

Factors of Political Machines' Success: Russian Case

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## Abstract

Between 2000 and 2021, the political regime in Russia underwent significant transformations, presenting a compelling case for scholars of electoral authoritarianism. Elections emerged as pivotal not only for the regime and the opposition but also for the mechanism through which state resources were distributed to a select group of supporters. Such mechanisms, often referred to in academic literature as political machines or clientelistic exchanges, involve a complex web of interactions among politicians, intermediaries, and voters. While existing research on Russia provides some insights into aspects of clientelistic exchanges within the country, this dissertation seeks to offer a comprehensive analysis by examining all participants in these exchanges—their motivations, the resources at their disposal, and their dynamics across different electoral contexts within Russia. Thus, the overarching question of this study is: What does the Russian political machine look like when viewed as a unified mechanism? This research aims to identify the key actors involved, understand their motivations, and analyze how their interplay results in electoral gains for the dominant party (United Russia) and the incumbent (Vladimir Putin).

This research is comprised of three papers, each focusing on different aspects of the interactions and motivations within the political machine in Russia. Each paper introduces a theoretical framework for examining these relationships, offering unique perspectives on the dynamics at play. The first paper provides game-theoretic model explaining how the party distributes benefits to voters and how this influences their electoral preferences. The second paper examines the interplay between voters' motivations, the capabilities of brokers, and the party's preferences, which culminates in suboptimal electoral outcomes for the dominant party in an authoritarian regime. The third paper delves into the rent-seeking behavior that characterizes the cooperation between business entities and the regime, providing insight into the economic underpinnings of political machine.

This dissertation is organized as follows: It begins with an introduction that lays out the key definitions, summarizes the main arguments of the study, provides insight into the latest developments within the regime, and outlines potential avenues for future research on clientelism in Russia. Following this, the first paper presents findings from a nationwide survey in Russia, uncovering the respondents' preferences for different benefits and their related electoral decisions. The second paper investigates the influence of large businesses on elections through electoral mobilization strategies. It further demonstrates that although mobilization can increase voter turnout, the votes of mobilized individuals often favor the opposition. Lastly, the third paper explores the strategic collaboration between the dominant party's donors and the financial benefits they receive from the state, specifically through public procurement contracts.

This research contributes to the study of authoritarian regimes and, more specifically, clientelism, by employing statistical data and advanced quantitative methodologies. It is the aspiration of this work that scholars investigating clientelism in other non-democratic contexts with scarce data availability, as well as those focusing on Russia, can leverage the techniques and data presented here to uncover the covert mechanisms of political corruption.

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This work is dedicated to the country of my birth, which I immensely love and miss regardless of how often it breaks my heart. To democratic Russia with free and fair elections, a future where the issues I discuss are no longer prevalent. Perhaps one day, this project can serve as a somewhat valuable resource for those establishing democratic institutions in my homeland.

# Contents

<b>Copyright Notice</b>	<b>i</b>
<b>Abstract</b>	<b>ii</b>
<b>Acknowledgements</b>	<b>iii</b>
<b>Introduction</b>	<b>3</b>
<b>Paper 1: In acquaintance we trust: assessing electoral preferences of United Russia voters</b>	<b>10</b>
Introduction . . . . .	10
Literature review . . . . .	12
Electoral preferences model . . . . .	14
Data and operationalization . . . . .	17
Model formalization . . . . .	19
Results . . . . .	20
Robustness check . . . . .	24
Conclusion . . . . .	29
References . . . . .	30
Annex A: List of questions included to the omnibus survey . . . . .	32
Annex B: Covariate balance after matching . . . . .	37
Annex C: Codebook . . . . .	38
Annex D: Model Results . . . . .	41
Annex E: Model Results: with inducement . . . . .	136
<b>Paper 2: The big brothers: measuring influence of large firms on electoral mobilization in Russia</b>	<b>284</b>
Introduction . . . . .	284
Brokers and electoral mobilization . . . . .	286
Model specification . . . . .	289
Russian context . . . . .	291
Data collection . . . . .	294
Results . . . . .	295
Robustness checks . . . . .	300
Conclusion . . . . .	303
References . . . . .	305
Annex A: Distribution of observations . . . . .	309
Annex B: Regression tables . . . . .	310
Annex C: Robustness checks . . . . .	405
Annex D: Robustness checks regression tables . . . . .	410
Annex E: Robustness checks: salary test for turnout . . . . .	412
Annex F: Robustness checks: salary test for turnout. Regression Tables . . . . .	416
Annex G: Robustness checks: salary test for vote share . . . . .	439
Annex H: Robustness checks: salary test for vote share (Regression tables for UR and Putin . . . . .	443
Annex I: Robustness checks: state share in market interaction . . . . .	466

Annex J: Robustness checks: state share in market interaction. Regression table . . . . .	468
<b>Paper 3: Friends with benefits: exploring donors of the Russian ruling party</b>	<b>483</b>
Introduction . . . . .	483
Business actors support in authoritarian regimes . . . . .	484
Party resources . . . . .	487
Description of Russian donors . . . . .	488
Event study design . . . . .	490
Data . . . . .	494
Results . . . . .	497
Case studies . . . . .	501
Discussion and Conclusions . . . . .	501
References . . . . .	505
Annex A: Sector categories . . . . .	509
Annex B: Distribution of covariates by matched groups . . . . .	510
Annex C: Coefficients for general model . . . . .	511
Annex D: Coefficients for sectoral model . . . . .	512
Annex E: Coefficients for model with number of donations . . . . .	517
Annex F: Coefficients for income model . . . . .	519

## Introduction

This project explores the various dimensions of political machines within the Russian Federation as it consolidated its authoritarian regime. The period from early 2000-s to 2021 in Russian politics is usually characterized as electoral authoritarianism (Levitsky & Way, 2002; Ross, 2014; Saikonen, 2017; Schedler, 2013)<sup>1</sup>. While elections in the country have consistently been unfree and unfair by varying degrees, the Russian political landscape was evolving. This evolution is marked by a gradual escalation in repression, changes in the legal framework, intensified propaganda and a pivotal moment with constitutional amendments of 2020 and the full-scale invasion of Ukraine in February 2022, shifting country towards political regime model bearing similarities to those of Uzbekistan under Karimov or Tajikistan under Rahmon. While elections are still held in Russia, their role, as well as employed tactics have undoubtedly changed and should be studied further.

Prior to 2022, for nearly two decades, Russia's electoral system has been undergoing changes and modernization. Throughout this period, the autocrat, the dominant party, the opposition, and the voters have all been adapting through a process of trial and error in their strategies and tactics. This complex political evolution positions Russia as a rich case study for understanding electoral autocracies, which represent a majority of global authoritarian regimes ("The V-Dem Dataset", n.d.). However, this analysis should be approached with certain limitations in mind, acknowledging the unique context and constraints of the Russian experience. The case of Russia is scientifically fascinating, primarily because of the history, substantial resources, administrative and territorial complexity. The spectrum of techniques to sustain autocratic power, partially explored in this project, contributes to its scientific value. However, it is crucial to acknowledge that elections held within this consolidating autocracy are one of many components in a large and daunting machinery, which, under the regime's control, shows a blatant disregard for the value of individual lives. Throughout its history of regime consolidation, Russian state inflicted direct harm on a staggering number of people, both inside the country and abroad.

The increasing body of literature seeks to unpack the current dynamics of the regime through explanation of the popular support the regime seems to have (Driedger, 2023; Ishchenko & Zhuravlev, 2022; Rosenfeld, 2023). This project has shown that at least prior to full-scale invasion of Ukraine, support for the dominant party, United Russia, or for the autocrat, Vladimir Putin, often had little to no basis in ideological alignment. Instead, it appears to stem from a clientelistic network involving a multitude of actors and resources. Furthermore, even with electoral mobilization and the strategic distribution of resources

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<sup>1</sup>Throughout the text, I interchangeably use the terms "autocracy", "authoritarianism", and "dictatorship", as well as "autocrat" and "dictator" following the tradition established by Barbara Geddes and her co-authors (Geddes et al., 2014) in their writings on such regimes.

among different supporter groups, there is no assurance that votes will be cast in favor of United Russia or Putin. These findings indicate that over time, political machines may increasingly resort to fraudulent practices, a trend that seems to be reflected in the most recent presidential elections (Seibt, 2024). This also implies that electoral mobilization, even when coupled with resource distribution, is insufficient to eliminate the need for additional "security" measures such as ballot stuffing, electronic voting, compromising ballot secrecy, among others, to make sure the dominant party and the president could demonstrate good enough electoral support received.

This project consists of three papers observing each different aspect of Russian political machine and clientelistic practices it uses<sup>2</sup>. It is expected that political machine does not only serve dominant party United Russia, but also the autocrat operating on federal parliamentary and presidential elections. While both types of elections are at the national level, it is argued that the electoral mobilization, distribution and exchange of resources is organized in a decentralized manner - by local actors to involve voters in specific electoral districts or assigned to specific electoral committees. Hence the units of analysis are either voters, local brokers, or local electoral committees.

One of the the goals of this project was to demonstrate the link between different actors, their interdependence and their motivations, attempting to see the clientelistic exchange as pooled mechanism. Quite a lot of research was done on Russian case to overview and analyze some of the actors of electoral process in the country, as well as to identify schemes and mechanisms employed by dominant party. For instance, uncovering how resources in possession of political machines or politicians impact political machine organization, Tkacheva and Turchenko, 2022 showed how independent candidates in Russian elections balance between using their personal resources and striking deals with the regime to achieve a high electoral return. Reuter, 2010 focused on governors to demonstrate how they become part of the United Russia political machine depending on their access to autonomous political resources. Panov and Ross, 2016 look at distributive politics and its impact at electoral mobilization and turnout. Some studies look into specific employed mechanisms to assure electoral returns for United Russia. For example, Frye et al., 2014 highlighted the mechanism of workplace mobilization actively used by certain Russian enterprises. Forrat, 2018 demonstrates school teachers involvement in providing United Russia with expected electoral results. Several studies have explored ethnic electoral mobilization, attempting to explain the exceptionally high turnout and electoral success of United Russia in so-called "ethnic regions." Shkel, 2021 detailed the mechanism of an ethnic political machine in Bashkortostan, showing how local elites (e.g., heads of local administrations) play pivotal roles in electoral

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<sup>2</sup>Here and throughout the text, political machines are defined as organizations or network of actors mobilizing "electoral support by trading particularistic benefits to voters in exchange for their votes" (Stokes, 2005). It is also important to conceptually distinguish between political machines and clientelism. As Aspinall (**p.549**; Aspinall, 2014) notes, clientelism and political machines are very often used as interchangeable terms. Magaloni and Dimond (**p. 253**; Magaloni & Diamond, 2014) define clientelism as "an informal contractual arrangement between a political "patron" and his or her "clients" wherein the former delivers material benefits, jobs, and other personal favors and the latter respond with desirable forms of political behavior such as voting for the patron, mobilizing to protest, or even performing acts of violence to intimidate political rivals". Hence, in this work, by clientelism we understand certain practices embedded into patron-client relationships. Whereas political machines are seen as organizations involving certain actors (politicians, brokers and voters) and performing a set of clientelistic practices in order to achieve electoral goals

mobilization. Minaeva and Panov, 2023 demonstrated how the density of social networks in segregated ethnic communities addresses the commitment problem in electoral mobilization. Voters' side has also been overviewed in the context of Russian elections. Panov and Ross, 2023 found that voters who avoid electoral mobilization by political machines engage in performance voting when dissatisfied with their socio-economic conditions. Voters can also be either mobilized or demobilized strategically by political machine depending on the expectations about their electoral behavior (McAllister & White, 2017). Finally, some authors have attempted to provide a measure of the overall effectiveness of political machines in the regions. For example, Reuter et al., 2016 indicated that the state generally knows which political machines are effective and to what extent, as mayoral elections were maintained in cities where mayors control strong political machines. Tkacheva and Golosov, 2019 proposed an explanation for the cross-regional variation in United Russia's results through party primaries turnout.

This research project examines the dynamics between actors and the resources at their disposal, along with their preferences, with the goal of further exploring these elements across three distinct papers. The first paper explores the relationship between voters' preferences for various goods and their electoral decisions. Utilizing a nationally representative survey conducted prior to the 2021 parliamentary elections, it introduces a game-theoretic model that delineates the decision-making processes of both political parties and voters regarding resource allocation, expectations concerning the delivery of resources, and ultimately, voting strategies. This study establishes a connection between resources and voters' preferences, enriching the extensively explored area of how public and private goods are instrumentalized by clientelistic parties. The findings indicate that the core supporters of the leading party place a high value on personal wealth and connections to party members. In contrast, voters who emphasize the importance of social benefits and the overall economic growth tend to either abstain from voting or provide their support for opposition candidates. Additionally, the research reveals that there is only a slight difference in attitudes towards benefits between swing voters of United Russia and those who abstain from voting or vote for other parties. The paper makes an argument that persistent support of the dominant party seems to come from ability of the party to provide private benefits and the voters' expectation of them. This suggests that in the absence of such, the party would lose its support.

The second paper delves into the role of big firms as key players in Russia's political machinery. It investigates the spatial relationship between major enterprises and local electoral committees, proposing that companies situated near these committees significantly boost voter turnout in parliamentary and presidential elections. This suggests that electoral mobilization is achieved through the mobilization of the workforce. Moreover, this heightened turnout is linked to an increase in protest votes cast for candidates or parties seen as oppositional in each electoral cycle. However, this pattern disappears in scenarios where electoral monitoring is enhanced. For instance, in smaller communities with stronger local ties or where there is a higher risk of compromising ballot secrecy, there is a noticeable correlation between high voter turnout and support for the dominant party or incumbent. The paper proposes a theoretical model that explains why, within an authoritarian context, a political machine is inevitably constrained to suboptimal efficiency due to the motivations of both voters and brokers. The ruling party tends to engage with brokers possessing extensive networks, viewing them as reliable largely because of personal acquaintances. However, these

brokers often wield less influence over the voters. From the voters' perspective, the likelihood of the dominant party's victory is seen as high, diminishing any incentive to vote for it unless there is genuine support or a risk of compromising ballot secrecy. Consequently, this form of mobilization proves to be rather ineffective for the authoritarian regime in terms of vote share.

The third paper shifts focus to examine the private donors of the dominant party, without directly analyzing voter behavior through electoral outcomes. Its objective is to uncover the motivations behind private businesses' support for the party. Drawing on reasoning similar to that applied to donors in democratic contexts, the study anticipated finding both ideologically motivated supporters (those companies not seeking financial gains from their affiliation with United Russia) and opportunistic ones. Employing event study methodology to evaluate the impact of donations on the value of public procurement contracts awarded to donor companies, the paper reveals that opportunistic donors indeed experience a significant increase in contract values following their donations. The research further identifies a pattern among the types of companies that donate to United Russia, notably those in the construction sector and those in retail related to construction materials, as well as firms with higher annual revenues, are more likely to see benefits from their donations. In conclusion, the findings challenge the expectation of broad, ideologically based support for United Russia. Instead, the support from private companies is shown to stem from opportunistic and strategic motives.

Overall, these three papers have in their goal to discover the complexity of political machines, and in general demonstrate, that even with all the resources, pressure and mobilization, it often times fails to reach the goal of reaching high unanimous support of the dominant party and autocrat. Resources involved in rent-seeking of different actors are crucial to make the machine work, and in the absence of them it will inevitably collapse or would need to achieve its legitimacy through other means.

This dissertation intentionally concludes its scope in 2021 due to the evolving nature of the regime. Yet further study of clientelism and political machines in Russia could be done next, focusing on the most recent years. One of the new strategies used by the regime is remote electronic voting (*Distantsionnoe Elektronnoe Golosovanie DEG*). The use of DEG expanded since it was first introduced in 2019 to various regions and elections, culminating in the 2024 presidential elections where DEG was employed in 29 regions (Mislivskaya, 2023). Considerable concerns about increasing electoral frauds have been raised due to DEG expansion, citing a lack of transparency in the counting process Zayakin, 2021. Yet despite the consolidation of the authoritarian regime in the aftermath of constitutional amendments and the full-scale invasion of Ukraine, the regime introduces DEG sporadically, suggesting a reluctance to fully replace in-person elections. Potential explanations could include concerns about legitimacy and the importance of elections for gathering information, cooptation, and signalling stability to domestic elites. The regime's shift in strategies may reflect an evolving authoritarian regime, but elections still hold significance, especially when resources for repression are constrained due to military needs.

One of the potential future questions to explore is how does electronic voting change authoritarian elections and the public's relationship with the regime? Does it give autocrats like Putin ultimate electoral control, or can it backfire? It is evident that electronic voting may be less effective for legitimization compared to in-person voting. Consequently, many

Russian officials and the propaganda sources strive to portray DEG as no different from traditional in-person voting (United Russia, 2024). If these efforts fail, electronic voting has the potential to significantly diminish its crucial role as a mechanism of legitimization for the regime, both among the domestic population and the country's political elites. Furthermore, it is puzzling what serves as a source of observable variation in electronic voting results? How do the electoral machinery, the bureaucracy, and patronage networks adapt to using DEG? Drawing from elections where DEG has been implemented, it is evident that there is an observable variation in its outcomes(Central Election Commission of the Russian Federation, n.d.). However, the origin of this variability remains unclear. Furthermore, certain independent media outlets have reported instances of administrative mobilisation during the 2023 and 2024 elections (Meduza, 2021; Orlova et al., 2024). The efficacy of clientelistic exchange is closely tied to the monitoring capabilities of the political machine. Consequently, the general hypothesis is that the introduction of electronic voting has facilitated mobilisation strategies within political machines by addressing the perception of "controlled" voting among the electorate and, to some extent, by enhancing actual control, particularly over turnout.

Exploring the evolution of political machinery before 2022 and its subsequent developments could offer valuable insights and hopefully can be built on this study. This project aims to enhance the academic comprehension of the progression that led the Russian regime to its current state and the factors that contributed to its consolidation.

## References

- Aspinall, E. (2014). When brokers betray: Clientelism, social networks, and electoral politics in Indonesia. *Critical Asian Studies*, 46(4), 545–570.
- Central Election Commission of the Russian Federation. (n.d.). Remote Electronic Voting. Protocols of the territorial election commission on the results of remote electronic voting for each group of subjects of the Russian Federation.
- Driedger, J. J. (2023). Risk acceptance and offensive war: The case of Russia under the Putin regime. *Contemporary Security Policy*, 44(2), 199–225.
- Forrat, N. (2018). Shock-resistant authoritarianism: Schoolteachers and infrastructural state capacity in Putin's Russia. *Comparative Politics*, 50(3), 417–449.
- Frye, T., Reuter, O. J., & Szakonyi, D. (2014). Political machines at work voter mobilization and electoral subversion in the workplace. *World politics*, 66(2), 195–228.
- Geddes, B., Wright, J., & Frantz, E. (2014). Autocratic breakdown and regime transitions: A new data set. *Perspectives on politics*, 12(2), 313–331.
- Ishchenko, V., & Zhuravlev, O. (2022). Imperialist ideology or depoliticization? Why Russian citizens support the invasion of Ukraine. *HAU: Journal of Ethnographic Theory*, 12(3), 668–676.
- Levitsky, S., & Way, L. A. (2002). The rise of competitive authoritarianism. *J. Democracy*, 13, 51.
- Magaloni, B., & Diamond, L. (2014). Defining political clientelism's persistence. *Clientelism, Social Policy, and the Quality of Democracy*, 253–262.
- McAllister, I., & White, S. (2017). Demobilizing voters: Election turnout in the 2016 Russian election. *Russian Politics*, 2(4), 411–433.
- Meduza. (2021). On the First Day of Voting in the State Duma Elections, Abnormal Queues Formed at Polling Stations. According to Meduza, Budget Employees Were Asked to Vote by Noon.
- Minaeva, E., & Panov, P. (2023). Dense networks, ethnic minorities, and electoral mobilization in contemporary Russia. *Problems of post-communism*, 70(4), 376–387.
- Mislivskaya, G. (2023, December). Central Election Commission: 29 Regions Will Be Able to Use Online Voting in Presidential Elections.
- Orlova, K., Kuznetsov, P., & Serfimov, A. (2024). DEGnulis'.
- Panov, P., & Ross, C. (2016). Explanatory factors for electoral turnout in the Russian Federation: The regional dimension. *Demokratizatsiya: The Journal of Post-Soviet Democratization*, 24(3), 351–370.
- Panov, P., & Ross, C. (2023). 'Mobilized voting' versus 'performance voting' in electoral autocracies: Territorial variations in the levels of support for the systemic opposition parties in Russian municipalities. *Regional & Federal Studies*, 33(3), 333–354.
- Reuter, O. J. (2010). The politics of dominant party formation: United Russia and Russia's governors. *Europe-Asia Studies*, 62(2), 293–327.
- Reuter, O. J., Buckley, N., Shubenkova, A., & Garifullina, G. (2016). Local elections in authoritarian regimes: An elite-based theory with evidence from Russian mayoral elections. *Comparative political studies*, 49(5), 662–697.
- Rosenfeld, B. (2023). Survey research in Russia: In the shadow of war. *Post-Soviet Affairs*, 39(1-2), 38–48.

- Ross, C. (2014). Regional elections and electoral authoritarianism in Russia. In *Russia's authoritarian elections* (pp. 111–131). Routledge.
- Saikkonen, I. A. (2017). Electoral mobilization and authoritarian elections: Evidence from post-Soviet Russia. *Government and Opposition*, 52(1), 51–74.
- Schedler, A. (2013). *The politics of uncertainty: Sustaining and subverting electoral authoritarianism*. OUP Oxford.
- Seibt, S. (2024). ‘Shpilkin method’: Statistical tool gauges voter fraud in Putin landslide.
- Shkel, S. (2021). Why political machines fail: Evidence from Bashkortostan. *Demokratizatsiya: The Journal of Post-Soviet Democratization*, 29(1), 31–62.
- Stokes, S. C. (2005). Perverse accountability: A formal model of machine politics with evidence from Argentina. *American political science review*, 99(3), 315–325.
- Tkacheva, T., & Golosov, G. V. (2019). United Russia’s primaries and the strength of political machines in the regions of Russia: Evidence from the 2016 Duma elections. *Europe-Asia Studies*, 71(5), 824–839.
- Tkacheva, T., & Turchenko, M. (2022). Electoral success of independents under authoritarianism: Evidence from Russia’s local elections, 2014–2018. *Problems of Post-Communism*, 69(3), 270–281.
- United Russia. (2024, March). Elektronnoe golosovanie — udobno i bezopasno: Deputaty Gosдумы проголосовали на выборах Президента.
- The V-Dem Dataset. (n.d.).
- Zayakin, A. (2021, November). *DEG vs. UG: What Have We Learned About Electronic Voting in Russia?* (Tech. rep.). Liberal Mission Foundation. Edited by Kirill Rogov.

# In acquaintance we trust: assessing electoral preferences of United Russia voters

## Abstract

This paper presents a framework for analyzing the phenomenon of support for the dominant party in the Russian Federation leading up to the 2021 parliamentary elections. The paper differentiates among various categories of United Russia supporters to analyze how voters perceive benefits, aiming to comprehend how variations in preferences for these benefits affect electoral decisions. Using a national representative survey, the paper explores the distinction between voters who prioritize private benefits with those prioritizing public goods in their electoral decisions. The evidence suggests that core supporters of the dominant party value individual wealth and personal connections to party members, while voters who prioritize social benefits and overall economic development tend to abstain from voting or support opposition candidates. The findings also demonstrate that there is minimal variation in attitudes towards benefits among swing voters supporting United Russia and those employing different electoral tactics.

## 1 Introduction

When examining the sources of popular support in autocracies, one body of literature suggests that regimes maintain support through a combination of strategies such as co-optation, repression, legitimization, propaganda, and others (Gerschewski, 2015; Guriev & Treisman, 2022). Such approach sees regime as rational institution balancing between sticks and carrots depending on the amount and type of available resources (Pepinsky, 2009), extent of popular support (Holdo, 2019) and institutional design (Geddes et al., 2004). It also provides a comprehensive overview of instruments available to autocrat for power maintaining.

Another set of theories focuses on the use of positive incentives that regimes can employ to ensure support. Some literature focuses on the regime's strategies in redistributing rent (Gandhi & Przeworski, 2006; Mesquita et al., 2005), while other aims to differentiate between various types of benefits that the state could provide, including public and private goods (Diaz-Cayeros et al., 2016; Zavadskaya et al., 2017). Such approach overviews regimes durability through the lens of available resources and their redistribution. And while authoritarian government in this case is still viewed as rational actor with the set of preferences and limitation imposed by resources availability, the narrowed focus on redistribution allows to study in-depth arguably one of the crucial elements of regime's stability (Greene, 2010; Pepinsky, 2009).

Both approaches often neglect to consider the perspective of the voters involved. It is widely acknowledged in the literature that in competitive authoritarian regimes, voters have a degree of freedom in their decision-making process, albeit constrained by manipulation of electoral rules (Levitsky & Way, 2010; Schedler, 2006) as well as by their socio-economic status (Diaz-Cayeros et al., 2003). However, when discussing rent redistribution, there is limited understanding of voters' preferences regarding these resources and whether there are significant differences in the types of regime supporters based on the benefits they value. This paper aims to address this gap by examining the following research question: How do voters' preferences for different types of benefits influence their support for authoritarian regime?

To distinguish between types of supporters, we propose examining voters of the dominant party in the competitive authoritarian regime of Russia from 2016 to 2021 and categorizing them as either core or swing. Additionally, we aim to differentiate within the group of swing voters based on the set of options they choose from, such as voting for other parties or not voting at all. Proposed distinction follows well-established tradition in the literature about non-democratic regimes (Diaz-Cayeros et al., 2016; Pelke, 2020; Zavadskaya et al., 2017) and looks at the supporters of authoritarian government in their diversity. While it is expected that even in the absence of free and fair elections a proportion of the population supports the regime (i.e. autocrat or dominant party), authoritarian government can rarely rely purely on its ideological supporters and attempts to mobilize electoral support as wide as possible, implementing both positive and negative incentives in attempt to expand the share of supporters. These incentives may encompass a range of material benefits, directed either toward an individual or a collective, as well as direct electoral mobilization.

This paper aims to delve deeper into the perspective of voters and their preferences. By surveying voters on the types of benefits they prioritize when making electoral decisions, we seek to differentiate between: a) core and swing supporters of the dominant party (United Russia) b) swing supporters of the dominant party and voters of other parties participating in the 2016 and 2021 parliamentary elections, or non-voters, and c) voters who prioritize public goods and social welfare programs versus those who prioritize particularistic benefits and individual prosperity. Subsequently, we aim to determine whether there exists a distinct relationship between the types of benefits valued by voters and their electoral preferences. Drawing on the frameworks proposed by Diaz-Cayeros et al. (Diaz-Cayeros et al., 2016), Pelke (Pelke, 2020), Kitschelt and Wilkinson (Kitschelt & Wilkinson, 2007), and others, we anticipate that public goods and social welfare programs will have a greater importance for swing supporters of the dominant party, while particularistic benefits will be of particular interest to core supporters. We also assume that voters of other parties and non-voters have preferences similar to occasional supporters of United Russia. Additionally, we consider factors such as experiences of electoral inducement to assess whether preferences for certain types of benefits change under the influence of electoral pressure. We find reliable evidence that core supporters of United Russia indeed value particularistic benefits and individual wealth the most, while valuing public goods and social welfare programs drives voters to either be swing supporters of UR, other parties or abstain from voting at all. We also find that people abstaining from voting are quite similar in their preferences to swing supporters of the dominant party, proving the conditionality and instability of this support.

## 2 Literature review

How does the dominant party or autocrat incentivize different types of voters? For instance, Diaz-Cayeroz et al. (Diaz-Cayeros et al., 2016) propose a model of "portfolio diversification," according to which the party's allocation of public goods versus private transactions increases in localities with a lower proportion of core supporters. While particularistic benefits may be more effective in securing votes for the party, they do not target as many voters as the party may require (Diaz-Cayeros et al., 2016, p.83-84). Pelke (Pelke, 2020) suggests that these strategies also vary depending on the type of regime, since they are determined by electoral pressure. The author posits that ruling parties are more inclined to redistribute income and provide public goods in multiparty autocracies compared to autocracies with hegemonic party (Pelke, 2020, p.1304). Closed autocracies, according to the author, are the least likely to distribute public goods due to minimal electoral pressure. Weiss (Weiss, 2016) demonstrated that the emergence of electoral opponents in authoritarian settings prompts parties to prioritize programmatic appeals over particularistic ones. Mares and Young (Mares & Young, 2018) showed that core voters not only have greater access to various forms of particularistic benefits but also face threats and mobilization efforts before elections. This is facilitated by ballot secrecy, which enables parties to depend solely on known ideological supporters.

While the rationale behind party behavior is evident, what about the voters' perspective? Diaz-Cayeroz et al. (Diaz-Cayeros et al., 2016) propose the "conditional party loyalty" theory, suggesting that voters' support for the party depends on their history of interactions and the anticipated redistribution of benefits. This theory is particularly relevant in non-democratic contexts or developing countries and suggests that generally, voters are less responsive to public goods in terms of electoral returns. Instead, loyal core supporters remain committed in anticipation of particularistic benefits. Simultaneously, parties perceive them as less risky investments than swing voters, as they are more familiar to party brokers. Mares and Young (Mares & Young, 2018) suggest that core voters are more prone to electoral mobilization and negative inducements in anticipation of access to benefits they do not want to lose.

Another set of theories examines voter preferences from an individualistic versus collective perspective. To some extent, prioritizing private enrichment over public goods, and vice versa, reflects classical left versus right economic attitudes. The value of collective or individualistic benefits is also studied in relation to the level of democracy in the state. The findings are somewhat controversial: while some authors are able to link individualism to economic prosperity (Gorodnichenko & Roland, 2017), stronger democratic institutions (Gorodnichenko & Roland, 2021), and a negative attitude towards state interventions (Cai et al., 2020), others observe that democracies are more likely to adopt redistributive policies (Acemoglu & Robinson, 2006) and provide higher levels of public goods (Deacon, 2009), thereby resulting in lower inequality (Acemoglu et al., 2015).

Indeed, although authoritarian countries may implement redistributive policies, their efficacy is typically constrained by the poor quality of public institutions (Gel'man, 2017) and high levels of corruption (Pellegata, 2013). Conversely, unlike in democracies, authoritarian governments are not constrained in resources, as there is no competition for budget allocation between parties. Therefore, the limitation lies in the amount of state resources available,

determined by the economic performance of the country, as well as in the size of political elites and core supporters requiring share of rent to stay loyal (Mesquita et al., 2005). The dominant party or autocrat can access these resources without public scrutiny and allocate them as they deem necessary to garner substantial public support. This distribution is likely to be ineffective as a policy and does not guarantee electoral returns, but is able to target wider scope of population.

On the contrary, private benefits more directly target supporters (Diaz-Cayeros et al., 2016) and hold greater significance for authoritarian governments, as they serve to secure essential support (Bader et al., 2014). Logically, supporters should also recognize that in a state likely to be inefficient in delivering social welfare, it is more advantageous to align with the regime in exchange for private benefits. However, not everyone in an authoritarian state becomes a regime supporter; furthermore, authoritarian governments can often be unpopular. Why is this the case?

There are several potential explanations for disloyalty to authoritarian regimes (aside from power struggles within elites), including ideological divergence (Fernandes, 2007), reactions to repression (Escribà-Folch, 2013, p.547), and dissatisfaction with quality of life and economic performance (Magaloni & Wallace, 2008, p.5). Concurrently, political ambivalence or conditional loyalty views voters as rational actors who rely on interactions with the party and strategic signaling (Diaz-Cayeros et al., 2016). However, it remains unclear what exactly distinguishes voters who consistently act as core supporters of the dominant party or autocrat from those who provide periodic support. In other words, if people do not have critical ideological divergence with autocratic government, what prevents them from being core supporters?

Answering this question also involves resolving the "chicken-and-egg" dilemma and determining whether voters' values precede their political identification, or if it is politicians who shape the political preferences of their constituents through incentives and penalties. To a large extent, under authoritarian rule, this sequence is determined by the type of autocracy. Following the dichotomy proposed by Gerschewski (Gerschewski, 2023), an authoritarian regime may adopt a strategy of either over-politicization or depoliticization. While the former involves ideational legitimization and formal methods of co-optation, the latter is based on performance legitimization and various forms of co-optation (Gerschewski, 2023, p.16). Over-politicization entails winning over voters through ideological means, while depoliticization entails avoiding political engagement and simply ensuring that citizens are sufficiently satisfied to provide the necessary support.

In over-politicized autocracies, ideological indoctrination combined with repression is more likely to shape people's political stances, or what perceived as the "correct" political stances that voters are expected to either support or risk facing repression for diverging from. On the contrary, in depoliticized autocracies, there is no strong ideological framework, allowing room for voters to develop their set of political values and preferences based on state performance (Gerschewski, 2023, p.15). Unlike autocracies relying heavily on ideology, the electoral divide in depoliticized regimes is less likely to revolve around clear-cut dichotomies such as communism vs market economy or nationalism vs pluralism. Instead, it tends to center around the various goods and benefits provided by the state, resulting in cleavages based on the performance indicators of the authoritarian regime. Certainly, this set of preferences is likely to be influenced by the state's performance, indicating that individuals

who directly benefit from the dominant party are more inclined to value these benefits over others.

In a depoliticized autocracy, the electoral decisions of voters are believed to be influenced primarily by two factors: the distribution of resources by the dominant party or state, and the voters' evaluation of this distribution's quality, along with their preferences for different kinds of resources. It could be contended that individuals in dictatorships choose to vote or abstain for reasons that are not directly linked to the allocation of benefits. This discussion leads to the concept of legitimacy and its significance in competitive authoritarian regimes. In such systems, legitimacy is often associated with elections. Initially, it was assumed that elections served to legitimize autocrats in the eyes of the international community (Levitsky & Way, 2002, p.59). However, as non-democratic regimes have become more recognizable, contemporary literature suggests that elections primarily serve to legitimize authoritarian governments in the eyes of their populations and elites (Gandhi & Lust-Okar, 2009; Schedler, 2013, p.121). The strategic distribution of resources among various groups to secure their support is a fundamental aspect of electoral authoritarianism and plays a crucial role in shaping voting behavior. This is because it affects the level of legitimacy or popular support that an autocrat or dominant party can secure. This dynamic has been illustrated through the analysis of fiscal policy by Pepinsky (Pepinsky, 2007), campaign financing in Malaysia by Weiss (Weiss, 2016), the case of Mexico studied by Greene, Magaloni, Diaz-Cayeros, and Weingast (Diaz-Cayeros et al., 2003; Greene, 2007), and more broadly by Seeberg (Seeberg, 2018).

Hence, it is anticipated that in competitive authoritarian systems with a dominant party, the electoral outcomes are influenced by both the voters' perceptions and the party's strategic approach to resource distribution. Drawing extensively from the theoretical framework proposed by Diaz-Cayeros et al. (Diaz-Cayeros et al., 2016), we aim to introduce an alternative viewpoint by examining the voters' perspective in this distribution process. Specifically, we will analyze whether their preferences for various types of resources shape their voting behavior.

### 3 Electoral preferences model

Proposed model follows game-theoretic approach, reflecting signaling game with sequential equilibrium, in which players make decision one after another and the outcome depends on the sequence of choices made as well as beliefs of the players (Figure 1). We suggest that voters and a party make decisions based on the anticipation of the behavior of other player and their own preferences. Party's strategy is in maximizing electoral support, while voters strategy is in maximizing the preferential resources they get in return. To simplify the model we use binary dichotomies. The sequential equilibrium is supposed to provide us information not only about the most optimal outcome, but also off-equilibrium paths which would allow to assess preferences not only dominant party voters, but also voters of the other parties and non-voting strategy.

The following formula outlines the utility calculation for voters and party. Utility for party is defined by the proportion of voters responding to the offered goods, as well as their type (core or swing voters). The dominant party first and foremost wants to assure that core voters

receive necessary benefits and return their electoral support. Utility for voters incorporates their preferences for public versus private goods, as well as their perceptions of the quality of those goods or probability of having access to them, resulting in different voting options.

$$U(V) = \alpha \cdot Q_{\text{public}} + \beta \cdot Q_{\text{private}} - C$$

where:

- $U(V)$  is the utility for a voter from choosing a particular voting option.
- $\alpha$  represents the weight or preference the voter places on public goods.
- $\beta$  represents the weight or preference the voter places on private goods.
- $Q_{\text{public}}$  is the perceived quality of public goods and services provided or promised by the voting option.
- $Q_{\text{private}}$  is the perceived quality of private goods and services provided or promised by the voting option.
- $C$  any cost associated with the voting option, such as skepticism regarding political promises (kept constant for all voters).

$$U(P) = \sum_{i \in \{\text{public, private}\}} pV_i \cdot vV_i$$

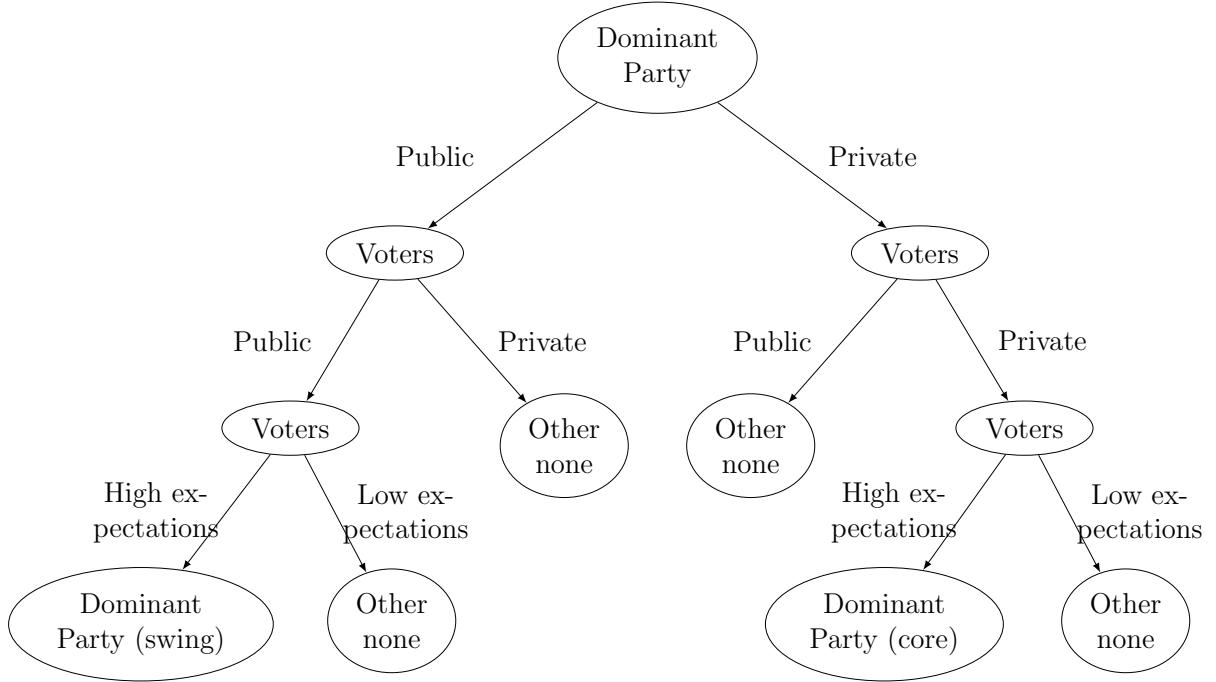
where:

- $U(P)$  is the utility for the political party.
- $pV_i$  represents the proportion of voters responding positively to the signal  $i$  (either public or private).
- $vV_i$  is the value the party assigns to attracting voters with preference  $i$ , which could include considerations of loyalty and ideological alignment.

We also assume that the game is not played simultaneously but rather sequentially, expecting that the voters make the move based on party's distribution of goods prior to elections. We also expect different types of goods to have different weights in terms of probability for electoral return. Following Diaz-Cayeros et al. (Diaz-Cayeros et al., 2016, p.75-81) we expect private goods to be more effective hence bringing core voters for electoral support of the dominant party, while public goods would result in occasional voting for the dominant party (or swing voters).

We begin by positing that the dominant party has both public and private goods at its disposal for distribution, which are then targeted toward distinct voter groups (Figure 1). Voter preferences vary, with some leaning towards social programs (indicative of a preference for public goods), while others prioritize personal gain (showing a preference for private goods). Based on these preferences, voters might immediately opt to support an alternative party or choose not to vote at all. Alternatively, they might evaluate the quality of the

Figure 1: Decision Tree Model of Voter and Party Interaction



goods provided or the likelihood of accessing these goods. Should voters perceive a high probability of access and satisfactory quality, they are inclined to support the dominant party. Conversely, if their expectations are not met in terms of accessibility or quality, they may decide either not to vote or to vote for a different party. Additionally, it's anticipated that the dominant party assigns varying importance to the distribution of these goods, prioritizing the allocation of private goods over public ones.

Therefore the following hypothesis are formulated to further test in the analysis:

H1: Voters who favor private goods and perceive both the quality and accessibility of these goods as high tend to consistently choose United Russia as their preferred party. Such individuals are considered core supporters of United Russia.

H2: Voters with a preference for public goods, who also rate the quality and accessibility of these goods highly, are inclined to choose United Russia as their party of choice, albeit on an occasional basis. These voters are identified as swing supporters of United Russia.

H3: Whether a voter's preference lies with public or private goods, if they judge the quality and accessibility of these goods to be poor OR they do not have a preference for the goods being offered, they are likely to support an alternative party or abstain from voting entirely.

## 4 Data and operationalization

The analysis presented in this paper is based on a survey conducted by the Levada Analytical Center in August 2021, a month before the federal parliamentary elections. This survey was incorporated into Levada's monthly omnibus poll, which is a nationwide survey covering both urban and rural populations across 56 of Russia's 85 regions ("Levada Omnibus Survey", n.d.). The regions not included in the survey are those that are hard to access, such as the Far North and certain areas of Siberia, which altogether account for less than 2% of the country's population. The methodology employed for this omnibus survey is a multi-stage, stratified, nationwide probability sample. The survey reached a total of 1,600 respondents, all of whom are over 18 years of age. It intentionally excludes certain population groups: military personnel (1% of the population), individuals who are convicted or imprisoned (0.8-1% of the population), homeless individuals (1-1.5% of the population), and those living in rural settlements with fewer than 50 inhabitants (around 1% of the population). The statistical margin of error for the survey is approximately 3.4%. Interviews were conducted face-to-face at the respondents' places of residence, and efforts were made to include both employed and unemployed individuals by scheduling interviews during weekends or weekday evenings. Various techniques were employed to verify the data collected, including route map checks, selective interview confirmations via phone or return visits, recording controls, and statistical tests. The survey questionnaire, detailed in Annex A, consisted of 26 questions in total, including 15 demographic questions and 11 questions regarding electoral preferences.

To determine the outcome variable of interest, we analyze responses to two survey questions regarding voting behavior in 2016 and the forthcoming 2021 elections:

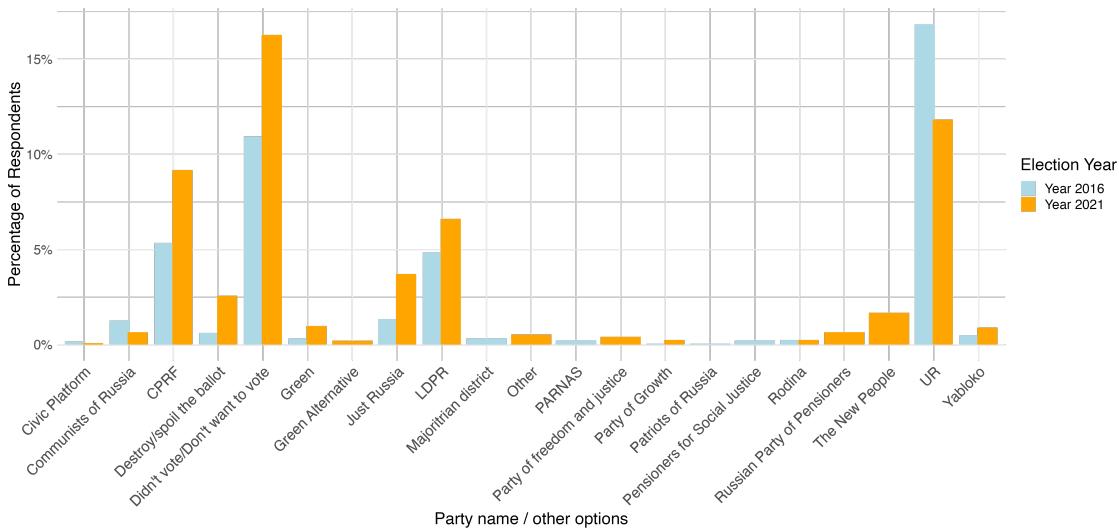
1. If the elections to the State Duma happened this Sunday, would you participate in voting? If yes, which of the parties would you vote for – or would you come to the elections to destroy/take the ballot with you?
2. For which party did you vote for on the last State Duma elections in 2016?

We categorize respondents as either core or swing voters for United Russia based on whether they voted for United Russia in both elections or just once. Individuals who chose not to vote in both elections are classified as non-voters. Those who consistently voted for parties other than United Russia are labeled as other party voters. For clarity and precision in our analysis, each regression model narrows down the sample to specific categories, such as comparing core versus swing voters or United Russia voters versus non-voters. Figure 2 presents the distribution of answers for both 2021 and 2016.

The main predictors are defined through the following questions:

1. How important is party's input into infrastructural development of your city/region/country for you voting decision? (1-not important; 6-the most important)
2. How important is party's input into economic development of your city/region/country for you voting decision? (1-not important; 6-the most important)
3. How important is party's input into social benefits provision for you voting decision? (1-not important; 6-the most important)

Figure 2: Party preferences of voters (2016-2021 Federal Duma Elections)



4. How important are your personal ties and connections to the party representatives for your voting decision? (1-not important; 6-the most important)
5. How important is your own economic wealth when deciding which party to support? (1-not important; 6-the most important)

For the purpose of facilitating matching, we converted these categorical variables into binary format, assigning a value of 1 to the first three levels: very important, rather important, and somewhat important.

The variables are crafted to identify the different types of goods valued by respondents. For public goods, such as social benefits, economic improvements, or infrastructural development, the categorization is relatively straightforward, as these are universally accessible benefits. However, capturing private goods—defined by Diaz-Cayeroz et al. (Diaz-Cayeros et al., 2016) as excludable, particularistic transfers like cash benefits, credits, land, and gifts—poses a challenge. Directly querying respondents about receiving such specific benefits in a survey might encourage untruthful responses. To address this, we suggest employing indirect measures, such as inquiries about individual wealth and personal connections to party members. We assume that personal ties to party members could serve as an effective indicator for potential access to exclusive benefits. Meanwhile, assessing individual wealth helps distinguish between those who prioritize social benefits and those inclined towards personal enrichment.

Clearly, voters may face coercion or pressure to vote for a specific party. To ensure that voters' electoral choices are not primarily swayed by different types of electoral inducements, relevant question has also been incorporated into the survey. The responses to this question serve as a means to perform a robustness check on the primary model, enhancing the reliability of our analysis.

## 5 Model formalization

The initial stage of the analysis involved matching to ensure that there was no inherent bias due to omitted variable. Although matching is primarily employed in experimental design studies, it also serves as a valuable technique in non-experimental research, including those that utilize representative surveys (D’Orazio et al., 2012; Lenis et al., 2019). Matching should allow balancing samples by predictor to assure no statistically significant difference because of covariates. Considering that many factors can impact electoral preferences besides attitude towards certain goods, we want to make sure none of them interfere with statistical relationship between main predictor and outcome variable.

Various methods are available for conducting matching in research, such as propensity score matching, subclassification, stratification, among others. The dataset in this study, while not overly large, contains a diverse array of demographic variables suitable for matching. These variables include both categorical and numerical types, making it feasible to either apply propensity score or full subclassification matching. Subsequently, their effectiveness in matching was evaluated and compared (Annex B). The covariates used for matching were age, sex, average income, education level, employment type, family size, locality size, and marital status. It is anticipated that any of these variables could significantly influence voting behaviors. Full subclassification matching appears to present on average higher precision based on both absolute standardized mean differences and Kolmogorov-Smirnov statistics.

Next after the matching the logistic regression is applied with the following computation of odds ratio. To assure that even after matching the set of demographic covariates does not neglect the effect of the main predictor (since not all samples have perfect matching outcome), we use interaction effect between the main predictor (attitude towards certain types of goods) and other covariates. Therefore the regression formula is the following:

$$\begin{aligned} \text{Logit}(P(\text{type of voter} = 1)) &= \beta_0 + \beta_1 \cdot \text{attitude towards goods} = 1 \\ &+ \sum \beta_i \cdot X_i \\ &+ \beta_{\text{interaction}} \cdot (\text{attitude towards goods} = 1 \times X_i) \end{aligned} \tag{1}$$

<sup>1</sup>

Where:

- $\text{Logit}(P(\text{type of voter} = 1))$  is the log-odds of the dependent variable `type of voter` being 1.
- $\beta_0$  is the intercept.
- $\beta_1 \cdot \text{attitude towards goods}$  represents the main effect of attitude towards goods variable.
- $\sum \beta_i \cdot X_i$  denotes the main effects of the covariates included in the model such as sex, age, education, employment status, marital status, average income, location size, and the number of family members.

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<sup>1</sup>The results of generalized Logit Model are presented in Annex D: Model Results. The list of predictors with respective baseline values are presented in Annex C: Codebook

- $\beta_{\text{interaction}} \cdot (\text{attitude towards goods} \times X_i)$  indicates the interaction terms between **attitude towards goods** and each of the other covariates in the model.

Next we calculate the marginal contrast for attitude towards goods, which is computed as follows:

**1. Predicted Probability with attitude towards goods = 1:**

$$\hat{P}(Y = 1 | \text{attitude towards goods} = 1, X = x_i) = \text{logit}^{-1}(\beta_0 + \beta_1 \cdot 1 + \sum_{j=2}^p \beta_j x_{ij})$$

**2. Predicted Probability with attitude towards goods = 0:**

$$\hat{P}(Y = 1 | \text{attitude towards goods} = 0, X = x_i) = \text{logit}^{-1}(\beta_0 + \beta_1 \cdot 0 + \sum_{j=2}^p \beta_j x_{ij})$$

**3. Marginal Contrast for Each Observation:**

$$\begin{aligned} \Delta \hat{P}(Y = 1 | X = x_i) &= \hat{P}(Y = 1 | \text{attitude towards goods} = 1, X = x_i) \\ &\quad - \hat{P}(Y = 1 | \text{attitude towards goods} = 0, X = x_i) \end{aligned}$$

**4. Average Marginal Contrast:**

$$\Delta \hat{P}_{\text{avg}}(Y = 1) = \frac{1}{N} \sum_{i=1}^N \Delta \hat{P}(Y = 1 | X = x_i)$$

**5. Transforming the Average Marginal Contrast (if needed):**

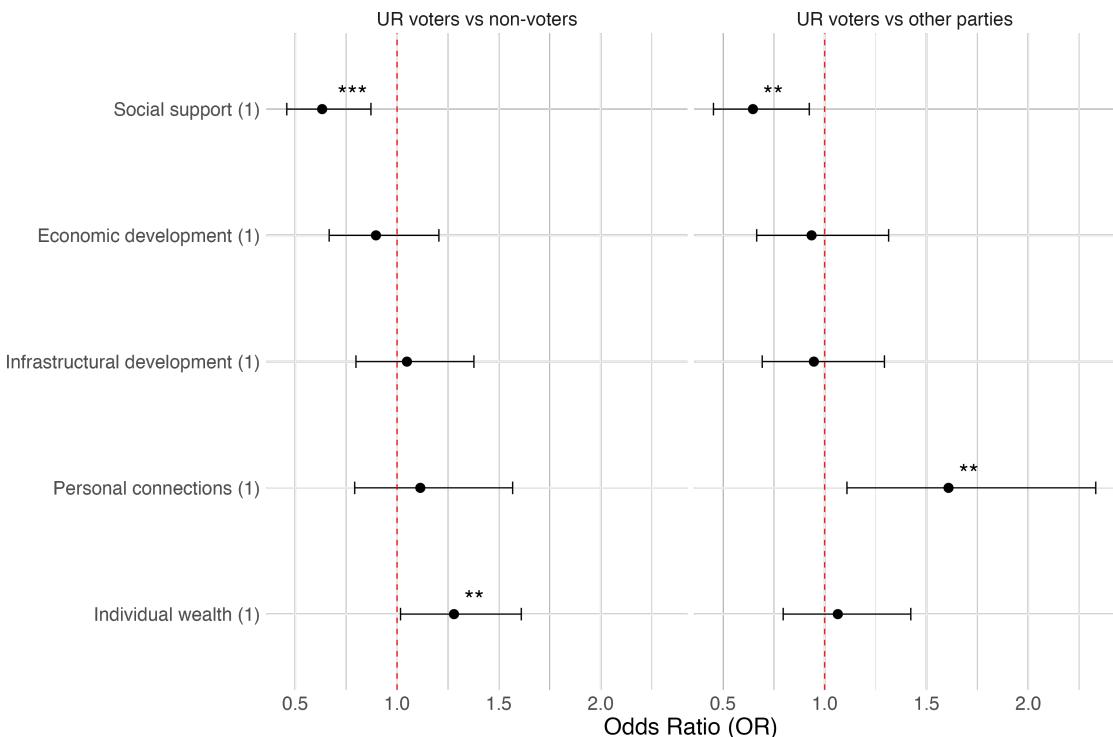
$$\text{Transformed Contrast} = \exp(\Delta \hat{P}_{\text{avg}}(Y = 1))$$

The results presented in the following section (estimate and confidence intervals) are the average marginal contrast of the variable attitude towards goods on the response variable. The confidence interval represents the range of possible values for the average change in the log-odds of the outcome when predictor(attitude towards goods) changes from 0 to 1, averaged over the dataset.

## 6 Results

This study's initial model examines voter preferences, leading to a choice between supporting United Russia and abstaining from voting, or between United Russia and casting votes for alternative parties (see Figure 3). The underlying theory posits that individuals might opt for United Russia if they prefer receiving public or private benefits and believe these benefits will be distributed effectively.

Figure 3: Goods Preferences Among UR Voters



(a) The model presents estimated effects after matching. Model fit is done with logistic regression and subclass weights. The model is first fit for the outcome given the predictor and the covariates, and then estimates marginal effects with cluster-robust SEs. The graph presents marginal Odds Ratio (exponentiated log OR) by predictors (calculated as average marginal contrast of the variable attitude towards goods on the response variable). The confidence interval represents the range of possible values for the average change in the log-odds of the outcome when predictor(attitude towards goods) changes from 0 to 1, averaged over the dataset. Each predictor's sample was separately matched by the following covariates: sex, age, employment status, family size, marital status, average income and location size. (\*\*\*) denote significance at the 99% confidence level, (\*\*) at the 95%, and (\*) denote significance at the 90%

The model indicates that placing a high value on social benefits reduces the likelihood of someone being a United Russia voter by 35% and 37%, while it raises the likelihood of being a non-voter or voting for other parties by 65% and 63%, respectively. Conversely, valuing individual wealth increases the chances of voting for United Russia (as opposed to not voting) by 27%. This effect, however, does not apply when the choice is between United Russia and other parties. In such cases, having personal connections significantly boosts the likelihood of supporting United Russia by 60%.

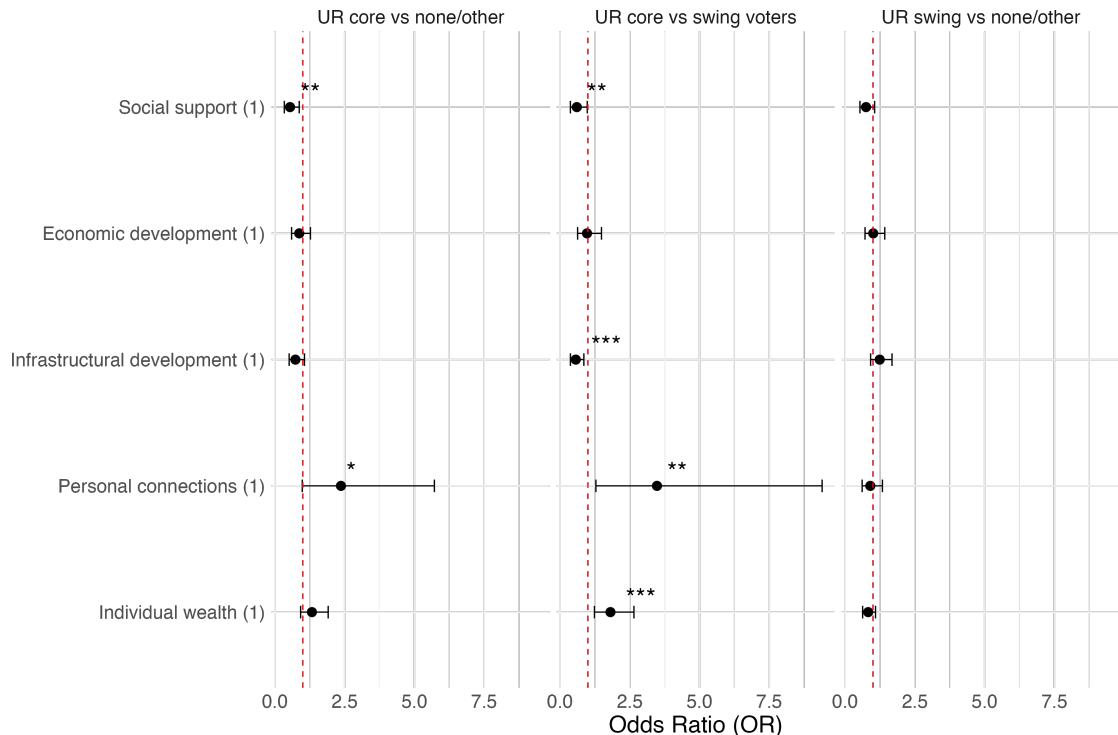
This implies that United Russia voters in general do not prioritize public goods, instead giving preference to individual wealth and personal connections with party members when deciding their vote. Interestingly, it is personal connections that influence the choice between United Russia and other parties, while the decision to abstain from voting is defined by valuing individual wealth. This might indicate that politically engaged individuals who choose to participate in elections are swayed by their relationships with party members to cast their vote for United Russia. People without such type of connections prefer abstaining when they are either dissatisfied with their personal economic prosperity, vote for United Russia if they perceive an alignment between the dominant party and the protection or promotion of their personal financial interests.

The next model aims to distinguish between core United Russia (UR) voters, swing UR voters, and those who vote for other parties or choose not to vote at all (see Figure 4). The theoretical foundation of this model posits that core UR voters are more inclined toward private goods, whereas swing voters are likely to prioritize public goods in their voting decisions. Additionally, it anticipates that the voting choice for UR, as compared to other strategies, may be significantly influenced by the type of goods voters prefer. Alternatively, if no distinct difference is observed, this could imply that voters' choices are primarily shaped by their perceptions of how effectively goods are distributed, rather than the type of goods per se.

The model reveals several key insights. Firstly, prioritizing social benefits while deciding for which party to vote for significantly reduces the likelihood of being a core United Russia (UR) voter by 46% and 40% in comparison to non-voters or voters for other parties, and to swing voters, respectively. On the other hand, having personal connections boosts the chances of supporting United Russia in these same groups by 136% and 247%, respectively. Furthermore, placing importance on individual wealth also enhances the likelihood of being a core UR voter compared to a swing UR voter by 80%, while valuing infrastructural development increases the odds for being swing voter by 44%. There appears to be no statistically significant difference in preferences for benefits among those distinguishing between UR swing voters and non-voters or voters for other parties.

These findings initially indicate that swing voters of United Russia (UR) are not significantly distinct from non-voters or voters for other parties. It is likely that factors other than preferences for certain goods motivate their decision-making process when choosing among these options. Conversely, core UR voters display tendencies aligned with those identified in the initial model, showing a preference for private benefits over public goods. The prioritization of social benefits tends to drive individuals towards voting for other parties, abstaining from voting, or becoming swing voters. This is further supported by the insignificant coefficients in the model comparing swing voters with non-voters or voters for other parties, indicating no substantial difference between occasionally voting for UR and either

Figure 4: Goods Preferences Among UR Swing and Core voters



(a) The model presents estimated effects after matching. Model fit is done with logistic regression and subclass weights. The model is first fit for the outcome given the predictor and the covariates, and then estimates marginal effects with cluster-robust SEs. The graph presents marginal Odds Ratio (exponentiated log OR) by predictors (calculated as average marginal contrast of the variable attitude towards goods on the response variable). The confidence interval represents the range of possible values for the average change in the log-odds of the outcome when predictor(attitude towards goods) changes from 0 to 1, averaged over the dataset. Each predictor's sample was separately matched by the following covariates: sex, age, employment status, family size, marital status, average income and location size. (\*\*\*) denote significance at the 99% confidence level, (\*\*) at the 95%, and(\*) denote significance at the 90%

not voting or supporting other parties.

However, a notable exception involves the role of infrastructural development. Valuing infrastructural development significantly influences an individual's likelihood of being a swing rather than a core UR voter, though it does not have a similar impact when choosing between core voting for UR and not voting or voting for another party. Nor does it have a significant impact for the group choosing between occasional voting for UR and non-voting or voting for another party. This could potentially suggest that voters who value public goods but sometimes are dissatisfied with its delivery tend to vote for UR occasionally. Additionally, people tend to become core supporters of the UR party, rather than occasional voters, when they place importance on both personal connections and personal wealth. However, prioritizing personal wealth alone does not distinctly separate UR's core supporters from non-supporters or those who vote for different parties. This indicates a pronounced distinction between loyal and swing UR voters, primarily grounded in their preferences for public versus private benefits.

## 7 Robustness check

Elections in authoritarian regimes are susceptible to various forms of manipulation. Our survey focuses on voters' preferences rather than on the actual electoral outcomes in specific localities, so the results should not be immune to the effects of electoral fraud. However, they could still be influenced by different types of electoral inducement that voters may encounter. It is possible that these inducements, rather than voters' preferences for different kinds of benefits, are what truly affect voting decisions. Participants were asked if they had experienced any form of inducement two months prior to elections, with options to indicate multiple types of inducement if necessary. To ensure the analysis is thorough, we introduced a binary variable that assigns a value of 1 if the voter has experienced any form of electoral inducement and interacted it with each type of benefit. The initial formula for the analysis is updated in the following way:

$$\begin{aligned} \text{Logit}(P(\text{type of voter} = 1)) = & \beta_0 + \beta_1 \cdot \text{attitude towards goods} = 1 + \beta_2 \cdot \text{electoral inducement} = 1 \\ & + \sum \beta_i \cdot X_i \\ & + \beta_{\text{interaction1}} \cdot (\text{attitude towards goods} = 1 \times X_i) \\ & + \beta_{\text{interaction2}} \cdot (\text{infrastructure development} = 1 \times \text{electoral inducement}) \end{aligned} \quad (2)$$

<sup>2</sup>

Where:

- $\text{Logit}(P(\text{type of voter} = 1))$  is the log-odds of the dependent variable **type of voter** being 1.
- $\beta_0$  is the intercept.

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<sup>2</sup>The results of Logit Model with inducement interaction are presented in Annex E: Model Results: with inducement. The list of predictors with respective baseline values are presented in Annex C: Codebook

- $\beta_1 \cdot \text{attitude towards goods}$  represent the main effects of the attitude towards goods.
- $\beta_2 \cdot \text{attitude towards goods}$  represent the effects of the electoral inducement.
- $\sum \beta_i \cdot X_i$  denotes the main effects of the covariates included in the model such as sex, age, education, employment status, marital status, average income, location size, and the number of family members.
- $\beta_{\text{interaction1}} \cdot (\text{attitude towards goods} \times X_i)$  indicate the interaction terms between **attitude towards goods** with each of the other covariates in the model.
- $\beta_{\text{interaction2}}$  indicates the interaction term between **attitude towards goods** and **electoral inducement**.

To compute the marginal contrasts for interaction terms, we create two new datasets where **electoral inducement** is set to 0 and 1, respectively.

- **For elect\\_induc = 0:**

$$\Delta \hat{P}(Y = 1 | \text{elect\_induc} = 0, X = x_i) = \hat{P}(Y = 1 | \text{infrastr\_d} = 1, \text{elect\_induc} = 0, X = x_i) - \hat{P}(Y = 1 | \text{infrastr\_d} = 0, \text{elect\_induc} = 0, X = x_i)$$

- **For elect\\_induc = 1:**

$$\Delta \hat{P}(Y = 1 | \text{elect\_induc} = 1, X = x_i) = \hat{P}(Y = 1 | \text{infrastr\_d} = 1, \text{elect\_induc} = 1, X = x_i) - \hat{P}(Y = 1 | \text{infrastr\_d} = 0, \text{elect\_induc} = 1, X = x_i)$$

The average marginal contrast for each condition is computed as follows:

- **For elect\\_induc = 0:**

$$\Delta \hat{P}_{\text{avg}}(Y = 1 | \text{elect\_induc} = 0) = \frac{1}{N} \sum_{i=1}^N \Delta \hat{P}(Y = 1 | \text{elect\_induc} = 0, X = x_i)$$

- **For elect\\_induc = 1:**

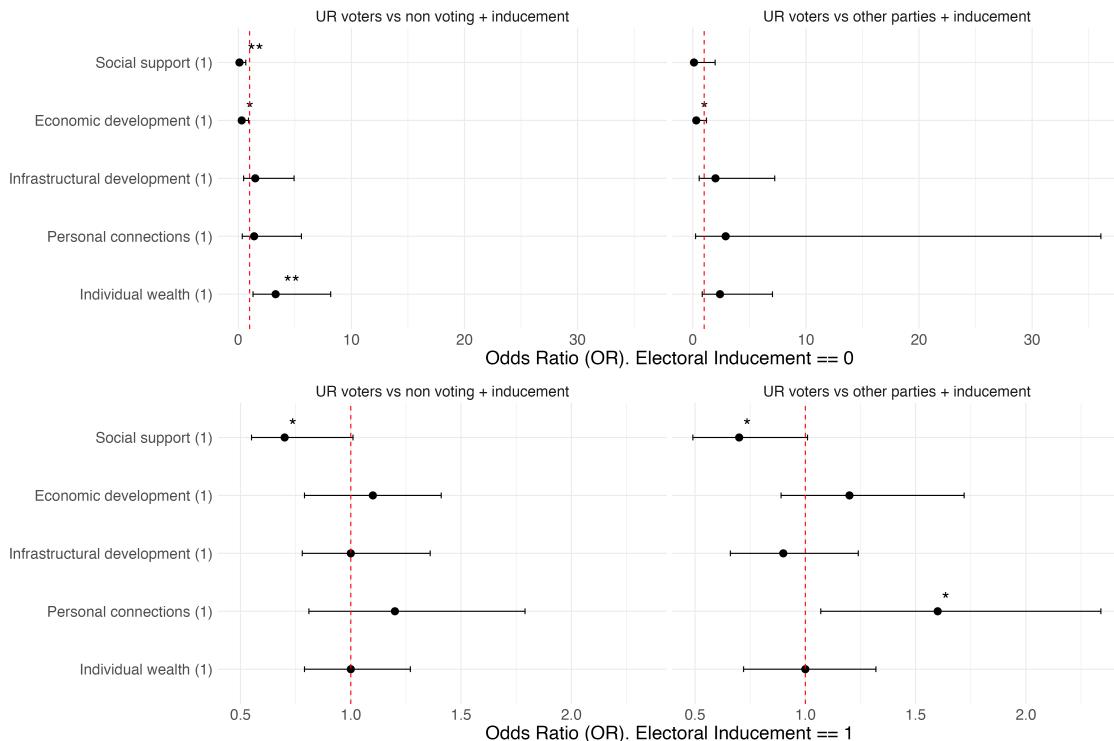
$$\Delta \hat{P}_{\text{avg}}(Y = 1 | \text{elect\_induc} = 1) = \frac{1}{N} \sum_{i=1}^N \Delta \hat{P}(Y = 1 | \text{elect\_induc} = 1, X = x_i)$$

The estimates are then exponentiated to transform them from the log-odds scale to the odds ratio scale:

- **For elect\\_induc = 0:**

$$\text{Transformed Contrast} = \exp(\Delta \hat{P}_{\text{avg}}(Y = 1 | \text{elect\_induc} = 0))$$

Figure 5: Goods Preferences Among UR Voters Under Electoral Inducement



(a) The model presents estimated effects after matching. Model fit is done with logistic regression and subclass weights. The model is first fit for the outcome given the predictor and the covariates, and then estimates marginal effects with cluster-robust SEs. The graph presents marginal Odds Ratio (exponentiated log OR) by predictors (calculated as average marginal contrast of the variable attitude towards goods on the response variable). The confidence interval represents the range of possible values for the average change in the log-odds of the outcome when predictor(attitude towards goods) changes from 0 to 1, averaged over the dataset. Each predictor's sample was separately matched by the following covariates: sex, age, employment status, family size, marital status, average income and location size. (\*\*\*) denote significance at the 99% confidence level, (\*\*) at the 95%, and(\*) denote significance at the 90%

- For `elect_induc = 1`:

$$\text{Transformed Contrast} = \exp(\Delta \hat{P}_{\text{avg}}(Y = 1 | \text{elect\_induc} = 1))$$

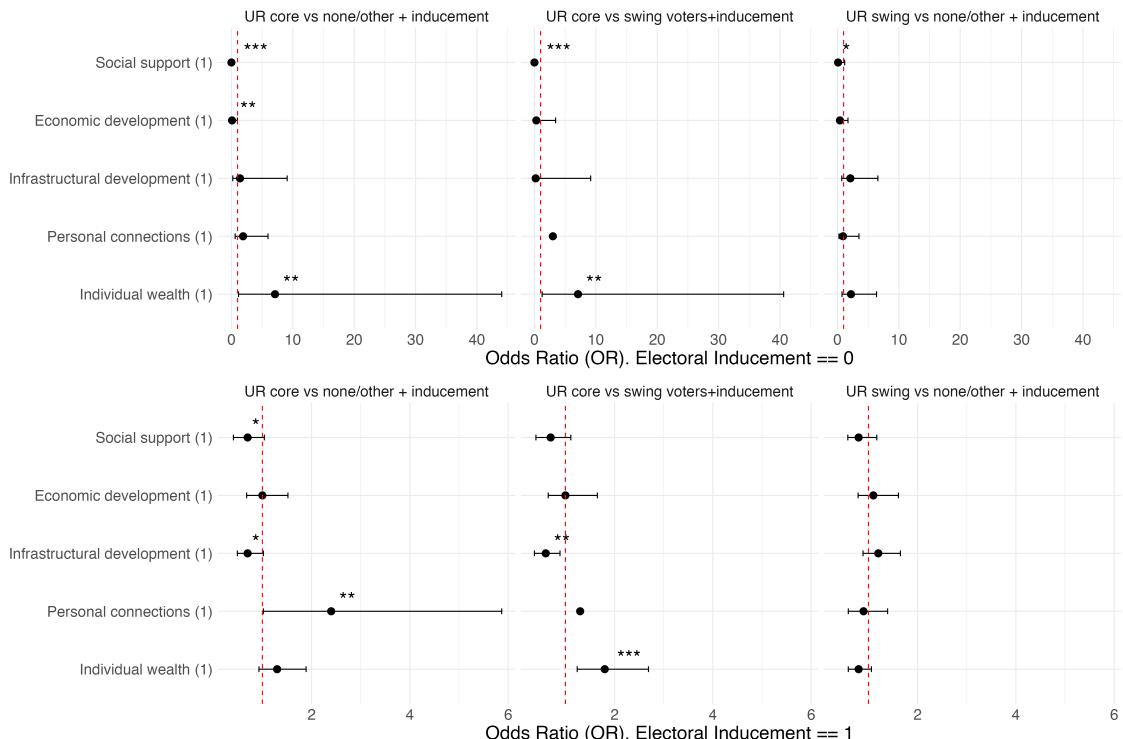
Initially, the analysis explored how electoral inducement influences the coefficients related to voters' choices between supporting United Russia and other alternatives (Figure 5). When voters are choosing between voting for UR and abstaining from voting, valuing social benefits continues to play a crucial role, reducing the likelihood of opting for UR by 33%. Similarly, for voters considering parties other than UR, placing importance on social support increases the probability of such a choice by 48%. However, individual wealth presents a contrasting picture in models that include an interaction term, particularly when decisions are between supporting UR and not voting; its effect is no longer statistically significant. In contrast, the value placed on personal connections maintains its significance, even with the interaction term accounted for, enhancing the likelihood of voting for UR by 65%. This suggests that prioritizing individual wealth together with experiencing electoral inducement diminishes UR's appeal as the primary choice for voters picking between UR and non-voting, indicating that both options are perceived as equally viable.

This variation in voting behavior can be attributed to how different voters interpret electoral inducements. For example, voters who attribute their personal wealth to the performance of the ruling party may reconsider their support if they encounter electoral coercion. This experience could lead them to question the necessity of voting for the dominant party, potentially resulting in abstention. Electoral inducements can be seen in different lights: as a positive gesture, a coercive tactic, or a form of corruption. If individuals genuinely believe their wealth results from a status quo that fosters personal prosperity, then inducements might highlight the system's unfairness. Conversely, personal connections, initially viewed as a type of favoritism, may not be negatively impacted by inducements. In this case, voters might perceive these inducements as unfair yet beneficial, in case they remain loyal. This perspective underscores the complex interplay between personal gain, perceptions of fairness, and loyalty within the electoral process.

Secondly, we examined how electoral inducements affect the choices of voters when distinguishing between being core or swing supporters of United Russia, as well as between being committed UR supporters, non-voters, or supporters of other parties, and core voters with the same alternatives (Figure 6). In this analysis, two notable deviations from the initial model were observed. Firstly, the significance of infrastructural development emerged at the 90% confidence level for those deliberating between staunch support for UR and other alternatives. Secondly, social support was found to be significant at the 90% confidence level for individuals weighing the option of being undecided UR supporters versus other possibilities.

Although a 90% confidence level is relatively low, the diversity and size of our sample prompt us to consider its implications. The effect of electoral inducements seems to narrow the distinction between core and swing United Russia supporters, as well as between swing UR supporters and those who either support other parties or choose not to vote. Interestingly, both swing voters and those leaning towards other parties or abstaining seem to place a higher value on public goods in various forms. It appears that when faced with electoral inducements, committed UR voters do not experience a challenge to their beliefs, as such inducements align with their initial preference for the dominant party. However,

Figure 6: Goods Preferences Among UR Core and Swing Voters Under Electoral Inducement



(a) The model presents estimated effects after matching. Model fit is done with logistic regression and subclass weights. The model is first fit for the outcome given the predictor and the covariates, and then estimates marginal effects with cluster-robust SEs. The graph presents marginal Odds Ratio (exponentiated log OR) by predictors (calculated as average marginal contrast of the variable attitude towards goods on the response variable). The confidence interval represents the range of possible values for the average change in the log-odds of the outcome when predictor(attitude towards goods) changes from 0 to 1, averaged over the dataset. Each predictor's sample was separately matched by the following covariates: sex, age, employment status, family size, marital status, average income and location size. (\*\*\* denote significance at the 99% confidence level, (\*\*) at the 95%, and(\*) denote significance at the 90%

for those who are undecided, electoral inducements might have the opposite effect, leading them to scrutinize the quality of goods and services provided by the state more critically. This scrutiny could distance them further from voting for UR. This is particularly evident in the case of swing UR voters who, when considering electoral inducements, may find their valuing of certain social benefits pushing them away from UR altogether.

## 8 Conclusion

This study explores how voters' perceptions of different types of goods influence their voting strategies. Theoretical frameworks led us to anticipate a clear divide between supporters of United Russia and those favoring other parties or opting not to vote. Furthermore, we expected to find distinctions in the preferences for public goods versus private benefits among core and swing UR supporters. The empirical findings support these hypotheses and offer insightful nuances to initial theoretical expectations.

Firstly, it is discovered that swing UR voters share similar goods preferences with non-voters or supporters of other parties, suggesting a less pronounced distinction in this regard. However, a broader analysis reveals that UR voters exhibit distinct preferences when choosing between abstaining and voting for other parties. Personal wealth emerges as a significant motivator for individuals to vote for UR instead of abstaining, whereas personal connections to party members are a strong predictor of choosing UR over competing parties. Additionally, there is a clear contrast between core and swing UR voters in the types of goods they prioritize: core supporters are significantly motivated by private, exclusive benefits, whereas swing voters show a preference for public goods, potentially expressing dissatisfaction with their delivery through voting for other parties or not voting at all.

These findings lead us to several significant insights. Firstly, the support of dominant party core voters appears to be strongly tied to their access to private goods. This form of support does not stem from ideological allegiance or contentment with the country's overall progress. It suggests that if these voters were to lose access to private benefits—whether due to scarcity of resources or a reallocation to other groups—they might swiftly shift their support away from the dominant party in search of alternative options. Secondly, there seems to be a negligible distinction between swing voters and those who either abstain from voting or support other parties. This observation challenges the notion of a sharp divide between supporters of the dominant party and other voters. Aside from the core United Russia supporters, who depend on exclusive benefits, the loyalty of other voters is much more susceptible to various influencing factors.

Following its full-scale invasion of Ukraine, Russia is undergoing a regime transformation, becoming more closed and ideologically driven. Concurrently, it's critical to acknowledge that the war has imposed resource constraints on the regime, due to sanctions and the increased necessity to allocate significant resources to other segments of the population, such as soldiers, propagandists, and law enforcement agencies. As a result, we can anticipate an impact on voter behavior and their perception of various types of goods. This situation also implies that in forthcoming elections, the Russian government may increasingly depend on artificial electoral mobilization and electoral fraud, as opposed to genuine electoral support.

## References

- Acemoglu, D., Naidu, S., Restrepo, P., & Robinson, J. A. (2015). Democracy, redistribution, and inequality. In *Handbook of income distribution* (pp. 1885–1966, Vol. 2). Elsevier.
- Acemoglu, D., & Robinson, J. A. (2006). *Economic origins of dictatorship and democracy*. Cambridge University Press.
- Bader, J., Grävingholt, J., & Kästner, A. (2014). Would autocracies promote autocracy? A political economy perspective on regime-type export in regional neighbourhoods. In *International politics and national political regimes* (pp. 81–100). Routledge.
- Cai, M., Murtazashvili, I., Murtazashvili, J., & Salahodjaev, R. (2020). Individualism and governance of the commons. *Public choice*, 184, 175–195.
- Deacon, R. T. (2009). Public good provision under dictatorship and democracy. *Public choice*, 139, 241–262.
- Díaz-Cayeros, A., Estévez, F., & Magaloni, B. (2016). *The political logic of poverty relief: Electoral strategies and social policy in Mexico*. Cambridge University Press.
- Díaz-Cayeros, A., Magaloni, B., & Weingast, B. R. (2003). Tragic brilliance: Equilibrium hegemony and democratization in Mexico. *Hoover Institution, Stanford University*.
- D’Orazio, M., Di Zio, M., & Scanu, M. (2012). Statistical matching of data from complex sample surveys. *Proceedings of the European Conference on Quality in Official Statistics-Q2012*, 29.
- Escribà-Folch, A. (2013). Repression, political threats, and survival under autocracy. *International Political Science Review*, 34(5), 543–560.
- Fernandes, T. (2007). Authoritarian regimes and pro-democracy semi-oppositions: The end of the portuguese dictatorship (1968–1974) in comparative perspective. *Democratization*, 14(4), 686–705.
- Gandhi, J., & Lust-Okar, E. (2009). Elections under authoritarianism. *Annual review of political science*, 12, 403–422.
- Gandhi, J., & Przeworski, A. (2006). Cooperation, cooptation, and rebellion under dictatorships. *Economics & politics*, 18(1), 1–26.
- Geddes, B., et al. (2004). Minimum-winning coalitions and personalization in authoritarian regimes. *Annual Meetings of the American Political Science Association, Chicago*.
- Gel’man, V. (2017). Political foundations of bad governance in post-Soviet Eurasia: Towards a research agenda. *East European Politics*, 33(4), 496–516.
- Gerschewski, J. (2015). The three pillars of stability: Legitimation, repression, and cooptation in autocratic regimes. In *Comparing autocracies in the early Twenty-first Century* (pp. 58–83). Routledge.
- Gerschewski, J. (2023). *The two logics of autocratic rule*. Cambridge University Press.
- Gorodnichenko, Y., & Roland, G. (2017). Culture, institutions, and the wealth of nations. *Review of Economics and Statistics*, 99(3), 402–416.
- Gorodnichenko, Y., & Roland, G. (2021). Culture, institutions and democratization. *Public choice*, 187, 165–195.
- Greene, K. F. (2007). *Why dominant parties lose: Mexico’s democratization in comparative perspective*. Cambridge University Press.
- Greene, K. F. (2010). The political economy of authoritarian single-party dominance. *Comparative political studies*, 43(7), 807–834.

- Guriev, S., & Treisman, D. (2022, April). *Spin Dictators: The Changing Face of Tyranny in the 21st Century*. Princeton University Press.
- Holdo, M. (2019). Cooptation and non-cooptation: Elite strategies in response to social protest. *Social Movement Studies*, 18(4), 444–462.
- Kitschelt, H., & Wilkinson, S. I. (2007). *Patrons, clients and policies: Patterns of democratic accountability and political competition*. Cambridge University Press.
- Lenis, D., Nguyen, T. Q., Dong, N., & Stuart, E. A. (2019). It's all about balance: Propensity score matching in the context of complex survey data. *Biostatistics (Oxford, England)*, 20(1), 147–163.
- Levada Omnibus Survey. (n.d.).
- Levitsky, S., & Way, L. A. (2002). The rise of competitive authoritarianism. *J. Democracy*, 13, 51.
- Levitsky, S., & Way, L. A. (2010). *Competitive authoritarianism: Hybrid regimes after the cold war*. Cambridge University Press.
- Magaloni, B., & Wallace, J. (2008). Citizen loyalty, mass protest and authoritarian survival. *Conference on Dictatorships: Their Governance and Social Consequences*, Princeton University.
- Mares, I., & Young, L. E. (2018). The core voter's curse: Clientelistic threats and promises in Hungarian elections. *Comparative Political Studies*, 51(11), 1441–1471.
- Mesquita, B. B. D., Smith, A., Siverson, R. M., & Morrow, J. D. (2005, January). *The Logic of Political Survival*. MIT Press.
- Pelke, L. (2020). Inclusionary regimes, party institutionalization and redistribution under authoritarianism. *Democratization*, 27(7), 1301–1323.
- Pellegata, A. (2013). Constraining political corruption: An empirical analysis of the impact of democracy. *Democratization*, 20(7), 1195–1218.
- Pepinsky, T. (2007). Autocracy, elections, and fiscal policy: Evidence from Malaysia. *Studies in Comparative International Development*, 42, 136–163.
- Pepinsky, T. (2009). *Economic crises and the breakdown of authoritarian regimes: Indonesia and Malaysia in comparative perspective*. Cambridge University Press.
- Schedler, A. (2006). *Electoral authoritarianism*. Lynne Rienner Publishers Boulder.
- Schedler, A. (2013). *The politics of uncertainty: Sustaining and subverting electoral authoritarianism*. OUP Oxford.
- Seeberg, M. B. (2018). Electoral authoritarianism and economic control. *International Political Science Review*, 39(1), 33–48.
- Weiss, M. L. (2016). Payoffs, parties, or policies: "Money politics" and electoral authoritarian resilience. *Critical Asian Studies*, 48(1), 77–99.
- Zavadskaya, M., Grömping, M., & i Coma, F. M. (2017). Electoral Sources of Authoritarian Resilience in Russia: Varieties of Electoral Malpractice, 2007–2016. *Demokratizatsiya: The Journal of Post-Soviet Democratization*, 25(4), 455–480.

## A List of questions included to the omnibus survey

List of questions included to the omnibus survey

1. Locality of interview (city, village)
  - 251 localities
2. Region
  - 56 regions
3. Sex
  - male/female
4. Age
5. Education
  - Primary or lower (7-8/9 classes of school)
  - High school (10/11 classes)
  - College education
  - Advanced college education
  - Incomplete university education
  - University education
6. If the elections to the State Duma happened this Sunday, would you participate in voting? If yes, which of the parties would you vote for – or would you come to the elections to destroy/take the ballot with you?
  - Communist party of Russian Federation (CPRF)
  - Russian ecological party “Green”
  - Liberal-democratic party of Russia
  - Political party “The new people”
  - United Russia
  - Political party “Just Russia – For Truth”
  - ”Russian United Democratic Party” YABLOKO
  - All-Russian political party ”Party of Growth”
  - Russian party of freedom and justice
  - Communist Party ”Communists of Russia”
  - Political party ”Civic Platform”
  - Ecological Party ”Green Alternative”

- All-Russian political party "Rodina"
  - "Russian Party of Pensioners for Social Justice"
  - Other
  - Destroy/spoil the ballot
  - I don't know which party to choose
  - I don't want to vote
  - I'm not sure if I would vote
7. For which party did you vote for on the last State Duma elections in 2016?
- All-Russian political party "Rodina"
  - Communist Party "Communists of Russia"
  - "Russian Party of Pensioners for Social Justice"
  - United Russia
  - Russian ecological party "Green"
  - Political party "Civic Platform"
  - Liberal-democratic party of Russia
  - Political Party "Party of People's Freedom" (PARNAS)
  - All-Russian political party "Party of Growth"
  - "Russian United Democratic Party" YABLOKO
  - Communist party of Russian Federation (CPRF)
  - Political Party "Patriots of Russia"
  - Political party "Just Russia"
  - Destroy/spoil the ballot
  - I voted only for candidate in majoritarian district
  - I didn't vote in 2016
  - I don't remember/don't want to reply
8. How important is party's input into infrastructural development of your city/region/country for you voting decision? (1-not important; 6-the most important)
9. How important is party's input into economic development of your city/region/country for you voting decision? (1-not important; 6-the most important)
10. How important is party's input into social benefits provision for you voting decision? (1-not important; 6-the most important)
11. How important are your personal ties and connections to the party representatives for your voting decision? (1-not important; 6-the most important)

12. How important is your own economic wealth when deciding which party to support?  
(1-not important; 6-the most important)
13. Do you participate (or plan to participate) in the ongoing electoral campaign of United Russia or another party? If yes, then in which role?
- Do not participate
  - Participate as electoral observer from UR
  - Participate as electoral observer from the other party
  - I participate in a role of a member of a precinct, district or territorial election committee from United Russia
  - I participate in a role of a member of a precinct, district or territorial election committee from the other party
  - I participate in the status of a member of the electoral campaign, an agitator or a volunteer
  - I cannot respond
14. In the last 2 months, have you experienced any inducement to vote?
- Have not experienced any inducement to vote in the last 2 months
  - Faced with inducement to vote by United Russia or candidates from United Russia
  - Faced with inducement to vote from the district administration, city authorities, regional administration
  - Encouraged to vote by superiors or colleagues
  - Faced an inducement to vote from another party (not United Russia)
  - Cannot respond
15. Did you vote on the last presidential elections on 18th of March, 2018?
- Yes/no
16. Whom did you vote for, or did you come to the elections to destroy/take the ballot with you?
- Sergey Baburin
  - Pavel Grudinin
  - Valdimir Zhirinivskiy
  - Vladimir Putin
  - Ksenia Sobchak
  - Grigoriy Yavlinskiy
  - Destroyed/took ballot with me

- Don't remember/don't want to respond

17. Type of employment

- Self-employed/independent entrepreneur
- Manager/administrator
- Technician
- Employee without education
- Laborer
- Student
- Pensioner
- Disabled person
- Stay-at-home person
- Unemployed (searching for job)
- Unemployed (not searching for job)

18. Marital status

- Married
- Not registered but live together
- Widow/widower
- Divorced
- Do not live together but not divorced
- Not married

19. How many people live with you including all the kids?

20. How many underaged kids live with you?

21. How can you describe wealth situation in your family?

- We don't even have enough money for food
- We have enough money for food, but not enough for clothes
- We have enough money for food and clothes, but not for buying more expensive things, such as a TV or a refrigerator
- We can buy some expensive things like fridge or TV, but we cannot buy a car
- We can buy a car, but we cannot say that we are not constrained in funds
- We can afford to buy anything

22. Monthly family income

23. Total family income for the last month

24. Per capita income

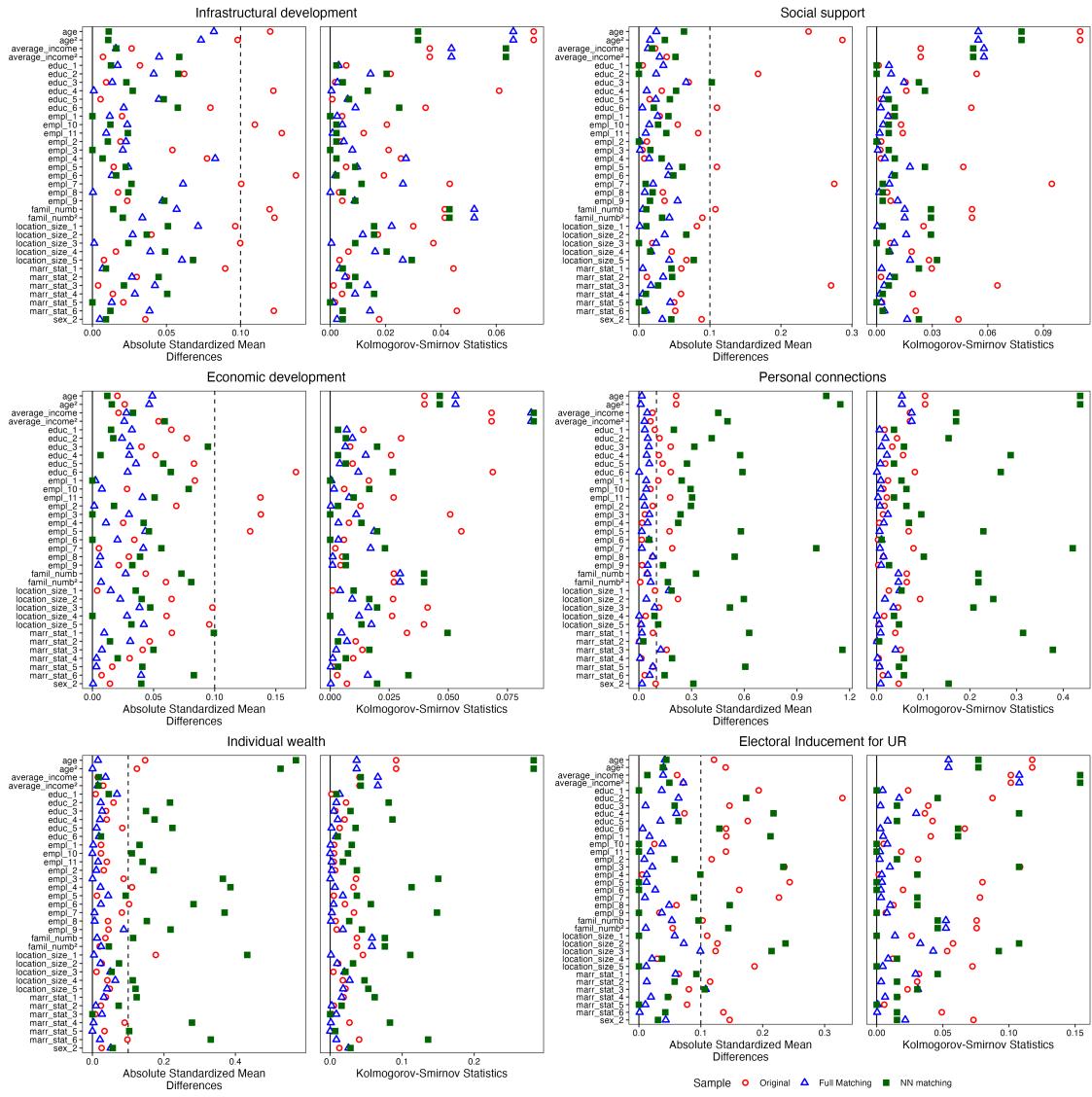
25. How frequently do you use internet?

- Every day
- Weekly
- One time a week
- Less than once a week
- Never use the internet

26. Size of locality

- Moscow
- Locality more than 500.000
- Locality from 100000 to 500000
- Locality less than 100000
- Village

## B Covariate balance after matching



## C Codebook

- **sex** - Sex of respondent
  - sex1: Male - baseline
  - sex2: Female
- **age** - Age of respondent (numeric)
- **educ** - Education level of respondent
  - educ1: Primary or lower, incomplete secondary school (7-8, now 9 grades) - baseline
  - educ2: Secondary school (10, now 11 grades)
  - educ3: Primary vocational education
  - educ4: Secondary vocational education
  - educ5: Incomplete higher education (at least 3 years of university)
  - educ6: Higher education
- **empl** - Employment status of respondent
  - empl1: Independent entrepreneur, self-employed - baseline
  - empl2: Manager, administrative worker
  - empl3: Specialist without managerial functions (with specialized education)
  - empl4: Employee without specialized education
  - empl5: Worker (including master, foreman), including in agriculture
  - empl6: Pupil, student
  - empl7: Retired (non-working) due to age/service
  - empl8: Retired (non-working) due to disability
  - empl9: Housewife, taking care of a child
  - empl10: Unemployed and looking for work
  - empl11: Unemployed and not looking for work
- **marr\_stat** - Marital status of respondent
  - **marr\_stat1**: Married - baseline
  - **marr\_stat2**: Not registered, but living together
  - **marr\_stat3**: Widower (widow)
  - **marr\_stat4**: Divorced
  - **marr\_stat5**: Living apart, but not divorced
  - **marr\_stat6**: Single, never married

- **famil\_numb** - Number of family members of respondent (numeric)
- **average\_income** - Average income per family member of respondent (numeric)
- **location\_size** - Size of the locality of respondent
  - **location\_size1**: Moscow - baseline
  - **location2** : *More than 500 thousand*
  - **location\_size3** : *From 100 to 500 thousand*
  - **location\_size4**: Cities up to 100 thousand
  - **location\_size5**: Rural areas
- **infrastr\_d** - attitude of respondent towards infrastructural development when making electoral choice
  - **infrastr\_d1**: Infrastructural development is important for respondent when making electoral choice
  - **infrastr\_d0**: Infrastructural development is not important for respondent when making electoral choice - baseline
- **socialsup\_d** - attitude of respondent towards social benefits when making electoral choice
  - **socialsup\_d1**: Social benefits are important for respondent when making electoral choice
  - **socialsup\_d0**: Social benefits are not important for respondent when making electoral choice - baseline
- **econdev\_d** - attitude of respondent towards economic development when making electoral choice
  - **econdev\_d1**: Economic development is important for respondent when making electoral choice
  - **econdev\_d0**: Economic development is not important for respondent when making electoral choice - baseline
- **personconnect\_d** - attitude of respondent towards personal connections to party members when making electoral choice
  - **personconnect\_d1**: Personal connections to party members are important for respondent when making electoral choice
  - **personconnect\_d0**: Personal connections to party members are not important for respondent when making electoral choice - baseline
- **indivwealth\_d** - attitude of respondent towards individual wealth when making electoral choice

- **indivwealth\_d1**: Individual wealth is important for respondent when making electoral choice
  - **indivwealth\_d0**: Individual wealth is not important for respondent when making electoral choice - baseline
- **elect\_induc** - the respondent experienced electoral inducement within two months prior to elections
  - **elect\_induc1**: the respondent experienced electoral inducement within two months prior to elections
  - **elect\_induc0**: the respondent did not experience electoral inducement within two months prior to elections - baseline

## D Model Results

Table 1: GLM model: UR voters vs other parties

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-2.68	1.01	-2.65	0.01	Infrastructural development	1137.52	1264.59	860	918
infrastr.d1	1.65	1.99	0.83	0.41	Infrastructural development	1137.52	1264.59	860	918
sex2	0.77	0.20	3.80	0.00	Infrastructural development	1137.52	1264.59	860	918
age	0.03	0.01	2.75	0.01	Infrastructural development	1137.52	1264.59	860	918
educ2	0.32	0.58	0.56	0.58	Infrastructural development	1137.52	1264.59	860	918
educ3	-0.59	0.69	-0.86	0.39	Infrastructural development	1137.52	1264.59	860	918
educ4	0.25	0.54	0.46	0.64	Infrastructural development	1137.52	1264.59	860	918
educ5	-1.92	0.97	-1.98	0.05	Infrastructural development	1137.52	1264.59	860	918
educ6	0.12	0.56	0.22	0.83	Infrastructural development	1137.52	1264.59	860	918
empl2	-0.11	0.64	-0.17	0.87	Infrastructural development	1137.52	1264.59	860	918
empl3	0.60	0.52	1.15	0.25	Infrastructural development	1137.52	1264.59	860	918
empl4	-0.25	0.54	-0.46	0.65	Infrastructural development	1137.52	1264.59	860	918
empl5	0.14	0.54	0.26	0.80	Infrastructural development	1137.52	1264.59	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl6	0.27	1.69	0.16	0.88	Infrastructural development	1137.52	1264.59	860	918
empl7	0.43	0.58	0.74	0.46	Infrastructural development	1137.52	1264.59	860	918
empl8	0.77	0.69	1.10	0.27	Infrastructural development	1137.52	1264.59	860	918
empl9	1.42	0.69	2.06	0.04	Infrastructural development	1137.52	1264.59	860	918
empl10	-0.25	0.79	-0.31	0.76	Infrastructural development	1137.52	1264.59	860	918
empl11	-0.10	1.19	-0.08	0.93	Infrastructural development	1137.52	1264.59	860	918
marr_stat2	-0.06	0.69	-0.09	0.93	Infrastructural development	1137.52	1264.59	860	918
marr_stat3	-0.31	0.29	-1.08	0.28	Infrastructural development	1137.52	1264.59	860	918
marr_stat4	-0.24	0.28	-0.85	0.40	Infrastructural development	1137.52	1264.59	860	918
marr_stat5	-15.26	971.75	-0.02	0.99	Infrastructural development	1137.52	1264.59	860	918
marr_stat6	0.42	0.32	1.31	0.19	Infrastructural development	1137.52	1264.59	860	918
average_income	0.00	0.00	1.01	0.31	Infrastructural development	1137.52	1264.59	860	918
location_size2	0.04	0.35	0.13	0.90	Infrastructural development	1137.52	1264.59	860	918
location_size3	-0.32	0.36	-0.87	0.38	Infrastructural development	1137.52	1264.59	860	918
location_size4	-0.41	0.36	-1.13	0.26	Infrastructural development	1137.52	1264.59	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	-0.06	0.36	-0.16	0.87	Infrastructural development	1137.52	1264.59	860	918
famil_numb	0.07	0.09	0.75	0.45	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:sex2	0.22	0.40	0.54	0.59	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:age	-0.01	0.02	-0.73	0.47	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:educ2	-0.37	1.02	-0.36	0.72	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:educ3	-0.02	1.23	-0.02	0.99	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:educ4	-0.70	0.94	-0.74	0.46	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:educ5	-13.72	977.34	-0.01	0.99	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:educ6	-1.20	1.02	-1.17	0.24	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl2	0.35	1.22	0.29	0.77	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl3	-1.26	0.99	-1.27	0.20	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl4	-1.08	1.06	-1.02	0.31	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl5	-1.15	1.01	-1.14	0.25	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl6	-14.57	1524.80	-0.01	0.99	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl7	-1.56	1.06	-1.47	0.14	Infrastructural development	1137.52	1264.59	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:empl8	0.39	1.35	0.29	0.78	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl9	-2.72	1.43	-1.90	0.06	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl10	-1.15	1.45	-0.79	0.43	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:empl11	14.76	1524.80	0.01	0.99	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:marr_stat2	-1.52	1.10	-1.37	0.17	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:marr_stat3	-0.16	0.59	-0.27	0.79	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:marr_stat4	-0.62	0.60	-1.03	0.30	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:marr_stat5	0.95	1808.12	0.00	1.00	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:marr_stat6	-1.55	0.71	-2.18	0.03	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:average_income	0.00	0.00	1.49	0.14	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:location_size2	0.85	0.70	1.21	0.23	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:location_size3	0.92	0.73	1.25	0.21	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:location_size4	1.44	0.70	2.07	0.04	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:location_size5	0.84	0.72	1.18	0.24	Infrastructural development	1137.52	1264.59	860	918
infrastr_d1:famil_numb	-0.09	0.18	-0.49	0.63	Infrastructural development	1137.52	1264.59	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-1.30	0.87	-1.48	0.14	Social Support	1106.58	1237.02	862	918
socialsup_d1	-2.34	2.66	-0.88	0.38	Social Support	1106.58	1237.02	862	918
sex2	0.57	0.18	3.19	0.00	Social Support	1106.58	1237.02	862	918
age	0.02	0.01	2.56	0.01	Social Support	1106.58	1237.02	862	918
educ2	0.10	0.49	0.20	0.84	Social Support	1106.58	1237.02	862	918
educ3	-0.33	0.59	-0.55	0.58	Social Support	1106.58	1237.02	862	918
educ4	-0.29	0.43	-0.67	0.50	Social Support	1106.58	1237.02	862	918
educ5	-1.17	0.85	-1.37	0.17	Social Support	1106.58	1237.02	862	918
educ6	-0.05	0.46	-0.11	0.91	Social Support	1106.58	1237.02	862	918
empl2	0.32	0.51	0.62	0.53	Social Support	1106.58	1237.02	862	918
empl3	-0.26	0.42	-0.63	0.53	Social Support	1106.58	1237.02	862	918
empl4	-0.72	0.46	-1.55	0.12	Social Support	1106.58	1237.02	862	918
empl5	-0.46	0.41	-1.11	0.27	Social Support	1106.58	1237.02	862	918
empl6	0.91	0.76	1.20	0.23	Social Support	1106.58	1237.02	862	918
empl7	-0.32	0.48	-0.66	0.51	Social Support	1106.58	1237.02	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl8	0.93	0.63	1.47	0.14	Social Support	1106.58	1237.02	862	918
empl9	0.00	0.73	0.01	1.00	Social Support	1106.58	1237.02	862	918
empl10	-0.33	0.50	-0.67	0.50	Social Support	1106.58	1237.02	862	918
empl11	2.26	0.84	2.68	0.01	Social Support	1106.58	1237.02	862	918
marr_stat2	-0.35	0.54	-0.65	0.52	Social Support	1106.58	1237.02	862	918
marr_stat3	0.05	0.34	0.14	0.89	Social Support	1106.58	1237.02	862	918
marr_stat4	0.06	0.25	0.24	0.81	Social Support	1106.58	1237.02	862	918
marr_stat5	-14.25	711.46	-0.02	0.98	Social Support	1106.58	1237.02	862	918
marr_stat6	0.27	0.29	0.96	0.34	Social Support	1106.58	1237.02	862	918
average_income	0.00	0.00	0.58	0.56	Social Support	1106.58	1237.02	862	918
location_size2	-0.70	0.32	-2.17	0.03	Social Support	1106.58	1237.02	862	918
location_size3	-0.29	0.33	-0.88	0.38	Social Support	1106.58	1237.02	862	918
location_size4	-0.37	0.34	-1.08	0.28	Social Support	1106.58	1237.02	862	918
location_size5	0.11	0.33	0.33	0.74	Social Support	1106.58	1237.02	862	918
famil numb	0.11	0.08	1.47	0.14	Social Support	1106.58	1237.02	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:sex2	0.44	0.52	0.83	0.40	Social Support	1106.58	1237.02	862	918
socialsup_d1:age	-0.01	0.03	-0.48	0.63	Social Support	1106.58	1237.02	862	918
socialsup_d1:educ2	0.28	1.62	0.17	0.86	Social Support	1106.58	1237.02	862	918
socialsup_d1:educ3	-0.81	1.95	-0.42	0.68	Social Support	1106.58	1237.02	862	918
socialsup_d1:educ4	-0.46	1.44	-0.32	0.75	Social Support	1106.58	1237.02	862	918
socialsup_d1:educ5	-15.98	564.25	-0.03	0.98	Social Support	1106.58	1237.02	862	918
socialsup_d1:educ6	-0.78	1.45	-0.53	0.59	Social Support	1106.58	1237.02	862	918
socialsup_d1:empl2	-1.71	1.40	-1.22	0.22	Social Support	1106.58	1237.02	862	918
socialsup_d1:empl3	0.21	1.07	0.20	0.84	Social Support	1106.58	1237.02	862	918
socialsup_d1:empl4	-0.49	1.23	-0.40	0.69	Social Support	1106.58	1237.02	862	918
socialsup_d1:empl5	0.30	1.08	0.28	0.78	Social Support	1106.58	1237.02	862	918
socialsup_d1:empl6					Social Support	1106.58	1237.02	862	918
socialsup_d1:empl7	0.95	1.21	0.78	0.43	Social Support	1106.58	1237.02	862	918
socialsup_d1:empl8	-0.77	1.93	-0.40	0.69	Social Support	1106.58	1237.02	862	918
socialsup_d1:empl9	2.22	2.04	1.09	0.28	Social Support	1106.58	1237.02	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:empl10	-0.22	1.41	-0.16	0.87	Social Support	1106.58	1237.02	862	918
socialsup_d1:empl11	-5.27	2.25	-2.34	0.02	Social Support	1106.58	1237.02	862	918
socialsup_d1:marr_stat2	-1.58	1.58	-1.00	0.32	Social Support	1106.58	1237.02	862	918
socialsup_d1:marr_stat3	0.37	1.02	0.36	0.72	Social Support	1106.58	1237.02	862	918
socialsup_d1:marr_stat4	0.29	0.76	0.38	0.70	Social Support	1106.58	1237.02	862	918
socialsup_d1:marr_stat5					Social Support	1106.58	1237.02	862	918
socialsup_d1:marr_stat6	-0.21	0.75	-0.27	0.78	Social Support	1106.58	1237.02	862	918
socialsup_d1:average_income	0.00	0.00	2.23	0.03	Social Support	1106.58	1237.02	862	918
socialsup_d1:location_size2	1.45	0.90	1.61	0.11	Social Support	1106.58	1237.02	862	918
socialsup_d1:location_size3	-0.49	0.99	-0.49	0.63	Social Support	1106.58	1237.02	862	918
socialsup_d1:location_size4	0.21	1.01	0.21	0.83	Social Support	1106.58	1237.02	862	918
socialsup_d1:location_size5	0.07	0.93	0.07	0.94	Social Support	1106.58	1237.02	862	918
socialsup_d1:famil_numb	0.49	0.25	2.00	0.05	Social Support	1106.58	1237.02	862	918
(Intercept)	-2.94	0.97	-3.04	0.00	Economic Development	1097.64	1218.74	862	918
econdev_d1	3.35	2.47	1.35	0.18	Economic Development	1097.64	1218.74	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
sex2	0.70	0.19	3.73	0.00	Economic Development	1097.64	1218.74	862	918
age	0.02	0.01	2.09	0.04	Economic Development	1097.64	1218.74	862	918
educ2	0.61	0.49	1.24	0.22	Economic Development	1097.64	1218.74	862	918
educ3	0.38	0.58	0.65	0.51	Economic Development	1097.64	1218.74	862	918
educ4	0.18	0.46	0.38	0.70	Economic Development	1097.64	1218.74	862	918
educ5	1.39	0.97	1.43	0.15	Economic Development	1097.64	1218.74	862	918
educ6	0.24	0.50	0.49	0.63	Economic Development	1097.64	1218.74	862	918
empl2	0.67	0.62	1.07	0.29	Economic Development	1097.64	1218.74	862	918
empl3	-0.14	0.49	-0.28	0.78	Economic Development	1097.64	1218.74	862	918
empl4	-0.71	0.53	-1.34	0.18	Economic Development	1097.64	1218.74	862	918
empl5	-0.03	0.50	-0.05	0.96	Economic Development	1097.64	1218.74	862	918
empl6	-0.77	1.30	-0.59	0.56	Economic Development	1097.64	1218.74	862	918
empl7	0.42	0.54	0.78	0.44	Economic Development	1097.64	1218.74	862	918
empl8	0.46	0.66	0.69	0.49	Economic Development	1097.64	1218.74	862	918
empl9	0.22	0.71	0.32	0.75	Economic Development	1097.64	1218.74	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl10	-0.40	0.60	-0.67	0.50	Economic Development	1097.64	1218.74	862	918
empl11	-0.88	0.66	-1.32	0.19	Economic Development	1097.64	1218.74	862	918
marr_stat2	-0.22	0.49	-0.46	0.65	Economic Development	1097.64	1218.74	862	918
marr_stat3	-0.47	0.28	-1.67	0.10	Economic Development	1097.64	1218.74	862	918
marr_stat4	-0.05	0.26	-0.18	0.86	Economic Development	1097.64	1218.74	862	918
marr_stat5	-14.70	406.16	-0.04	0.97	Economic Development	1097.64	1218.74	862	918
marr_stat6	-0.00	0.28	-0.01	1.00	Economic Development	1097.64	1218.74	862	918
average_income	0.00	0.00	1.99	0.05	Economic Development	1097.64	1218.74	862	918
location_size2	0.50	0.34	1.46	0.14	Economic Development	1097.64	1218.74	862	918
location_size3	0.24	0.34	0.71	0.48	Economic Development	1097.64	1218.74	862	918
location_size4	0.62	0.35	1.74	0.08	Economic Development	1097.64	1218.74	862	918
location_size5	0.56	0.36	1.58	0.11	Economic Development	1097.64	1218.74	862	918
famil_numb	0.20	0.08	2.47	0.01	Economic Development	1097.64	1218.74	862	918
econdev_d1:sex2	0.06	0.51	0.12	0.90	Economic Development	1097.64	1218.74	862	918
econdev_d1:age	0.02	0.02	0.78	0.44	Economic Development	1097.64	1218.74	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:educ2	-1.15	1.06	-1.09	0.28	Economic Development	1097.64	1218.74	862	918
econdev_d1:educ3	-3.47	1.38	-2.52	0.01	Economic Development	1097.64	1218.74	862	918
econdev_d1:educ4	-1.28	0.96	-1.33	0.18	Economic Development	1097.64	1218.74	862	918
econdev_d1:educ5	-15.76	913.86	-0.02	0.99	Economic Development	1097.64	1218.74	862	918
econdev_d1:educ6	-2.41	1.12	-2.15	0.03	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl2	-1.05	1.52	-0.69	0.49	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl3	0.80	1.29	0.62	0.53	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl4	0.04	1.39	0.03	0.98	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl5	-2.00	1.32	-1.51	0.13	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl6					Economic Development	1097.64	1218.74	862	918
econdev_d1:empl7	-1.32	1.39	-0.95	0.34	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl8	-2.41	1.81	-1.33	0.18	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl9	-0.30	1.86	-0.16	0.87	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl10	2.29	1.77	1.29	0.20	Economic Development	1097.64	1218.74	862	918
econdev_d1:empl11	1.75	2.10	0.83	0.41	Economic Development	1097.64	1218.74	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:marr_stat2	-0.81	1.47	-0.55	0.58	Economic Development	1097.64	1218.74	862	918
econdev_d1:marr_stat3	1.47	0.72	2.06	0.04	Economic Development	1097.64	1218.74	862	918
econdev_d1:marr_stat4	-0.35	0.73	-0.48	0.63	Economic Development	1097.64	1218.74	862	918
econdev_d1:marr_stat5					Economic Development	1097.64	1218.74	862	918
econdev_d1:marr_stat6	0.53	0.79	0.67	0.50	Economic Development	1097.64	1218.74	862	918
econdev_d1:average_income	-0.00	0.00	-0.23	0.82	Economic Development	1097.64	1218.74	862	918
econdev_d1:location_size2	-2.43	1.09	-2.23	0.03	Economic Development	1097.64	1218.74	862	918
econdev_d1:location_size3	-2.06	1.13	-1.83	0.07	Economic Development	1097.64	1218.74	862	918
econdev_d1:location_size4	-2.81	1.12	-2.51	0.01	Economic Development	1097.64	1218.74	862	918
econdev_d1:location_size5	-1.97	1.11	-1.77	0.08	Economic Development	1097.64	1218.74	862	918
econdev_d1:famil_numb	-0.03	0.20	-0.15	0.88	Economic Development	1097.64	1218.74	862	918
(Intercept)	-1.81	5.42	-0.33	0.74	Personal Connections	1144.84	1256.73	862	918
personconnect_d1	-0.71	5.50	-0.13	0.90	Personal Connections	1144.84	1256.73	862	918
sex2	1.70	1.10	1.55	0.12	Personal Connections	1144.84	1256.73	862	918
age	-0.01	0.04	-0.13	0.90	Personal Connections	1144.84	1256.73	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ2	3.71	2.74	1.35	0.18	Personal Connections	1144.84	1256.73	862	918
educ3	-2.71	3.37	-0.80	0.42	Personal Connections	1144.84	1256.73	862	918
educ4	0.07	2.60	0.03	0.98	Personal Connections	1144.84	1256.73	862	918
educ5	-15.50	2234.64	-0.01	0.99	Personal Connections	1144.84	1256.73	862	918
educ6	-1.05	2.74	-0.38	0.70	Personal Connections	1144.84	1256.73	862	918
empl2	0.74	2.08	0.36	0.72	Personal Connections	1144.84	1256.73	862	918
empl3	-1.33	1.45	-0.92	0.36	Personal Connections	1144.84	1256.73	862	918
empl4	-2.69	1.90	-1.41	0.16	Personal Connections	1144.84	1256.73	862	918
empl5	-3.13	1.98	-1.58	0.12	Personal Connections	1144.84	1256.73	862	918
empl6	-0.80	1.40	-0.57	0.57	Personal Connections	1144.84	1256.73	862	918
empl7	-1.72	1.80	-0.95	0.34	Personal Connections	1144.84	1256.73	862	918
empl8	-18.92	762.85	-0.02	0.98	Personal Connections	1144.84	1256.73	862	918
empl9	15.47	1554.73	0.01	0.99	Personal Connections	1144.84	1256.73	862	918
empl10	-1.91	2.66	-0.72	0.47	Personal Connections	1144.84	1256.73	862	918
empl11	0.99	8.48	0.12	0.91	Personal Connections	1144.84	1256.73	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-15.29	766.49	-0.02	0.98	Personal Connections	1144.84	1256.73	862	918
marr_stat3	1.98	1.16	1.71	0.09	Personal Connections	1144.84	1256.73	862	918
marr_stat4	-0.16	1.35	-0.12	0.90	Personal Connections	1144.84	1256.73	862	918
marr_stat5	-15.56	774.80	-0.02	0.98	Personal Connections	1144.84	1256.73	862	918
marr_stat6	-1.90	1.71	-1.11	0.27	Personal Connections	1144.84	1256.73	862	918
average_income	0.00	0.00	0.35	0.73	Personal Connections	1144.84	1256.73	862	918
location_size2	1.95	2.56	0.76	0.44	Personal Connections	1144.84	1256.73	862	918
location_size3	0.92	2.51	0.36	0.72	Personal Connections	1144.84	1256.73	862	918
location_size4	0.91	2.44	0.37	0.71	Personal Connections	1144.84	1256.73	862	918
location_size5	0.96	2.44	0.39	0.70	Personal Connections	1144.84	1256.73	862	918
famil_numb	0.15	0.47	0.32	0.75	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:sex2	-0.97	1.12	-0.87	0.39	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:age	0.02	0.05	0.51	0.61	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:educ2	-3.58	2.79	-1.29	0.20	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:educ3	2.43	3.42	0.71	0.48	Personal Connections	1144.84	1256.73	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:educ4	-0.15	2.64	-0.06	0.95	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:educ5	15.62	2234.64	0.01	0.99	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:educ6	0.78	2.78	0.28	0.78	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl2	-0.33	2.17	-0.15	0.88	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl3	1.86	1.53	1.22	0.22	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl4	2.54	1.97	1.29	0.20	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl5	3.28	2.05	1.60	0.11	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl6					Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl7	2.21	1.87	1.18	0.24	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl8	20.02	762.85	0.03	0.98	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl9	-14.81	1554.73	-0.01	0.99	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl10	2.09	2.74	0.76	0.45	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:empl11	-1.28	8.53	-0.15	0.88	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:marr_stat2	15.21	766.49	0.02	0.98	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:marr_stat3	-2.07	1.19	-1.73	0.08	Personal Connections	1144.84	1256.73	862	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:marr_stat4	0.06	1.38	0.05	0.96	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:marr_stat5					Personal Connections	1144.84	1256.73	862	918
personconnect_d1:marr_stat6	2.22	1.74	1.28	0.20	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:average_income	-0.00	0.00	-0.02	0.98	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:location_size2	-1.97	2.58	-0.76	0.45	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:location_size3	-0.91	2.54	-0.36	0.72	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:location_size4	-0.69	2.46	-0.28	0.78	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:location_size5	-0.59	2.47	-0.24	0.81	Personal Connections	1144.84	1256.73	862	918
personconnect_d1:famil_numb	-0.00	0.47	-0.00	1.00	Personal Connections	1144.84	1256.73	862	918
(Intercept)	-1.10	1.60	-0.69	0.49	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1	-1.40	1.88	-0.74	0.46	Individual Wealth	1122.14	1231.52	861	918
sex2	1.01	0.33	3.10	0.00	Individual Wealth	1122.14	1231.52	861	918
age	0.03	0.02	1.76	0.08	Individual Wealth	1122.14	1231.52	861	918
educ2	-1.47	0.72	-2.04	0.04	Individual Wealth	1122.14	1231.52	861	918
educ3	-1.77	0.91	-1.94	0.05	Individual Wealth	1122.14	1231.52	861	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ4	-1.98	0.66	-3.02	0.00	Individual Wealth	1122.14	1231.52	861	918
educ5	-15.82	710.58	-0.02	0.98	Individual Wealth	1122.14	1231.52	861	918
educ6	-2.63	0.70	-3.78	0.00	Individual Wealth	1122.14	1231.52	861	918
empl2	0.22	0.97	0.23	0.82	Individual Wealth	1122.14	1231.52	861	918
empl3	0.57	0.81	0.70	0.48	Individual Wealth	1122.14	1231.52	861	918
empl4	-0.31	0.90	-0.34	0.73	Individual Wealth	1122.14	1231.52	861	918
empl5	-0.60	0.84	-0.72	0.47	Individual Wealth	1122.14	1231.52	861	918
empl6	-0.55	1.25	-0.44	0.66	Individual Wealth	1122.14	1231.52	861	918
empl7	0.02	0.90	0.02	0.99	Individual Wealth	1122.14	1231.52	861	918
empl8	1.91	1.24	1.54	0.12	Individual Wealth	1122.14	1231.52	861	918
empl9	2.29	1.66	1.38	0.17	Individual Wealth	1122.14	1231.52	861	918
empl10	-1.45	1.42	-1.02	0.31	Individual Wealth	1122.14	1231.52	861	918
empl11	-0.43	1.84	-0.23	0.82	Individual Wealth	1122.14	1231.52	861	918
marr_stat2	-1.92	0.97	-1.98	0.05	Individual Wealth	1122.14	1231.52	861	918
marr_stat3	0.09	0.50	0.17	0.86	Individual Wealth	1122.14	1231.52	861	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat4	-1.20	0.54	-2.23	0.03	Individual Wealth	1122.14	1231.52	861	918
marr_stat5	-12.73	1115.63	-0.01	0.99	Individual Wealth	1122.14	1231.52	861	918
marr_stat6	0.37	0.54	0.69	0.49	Individual Wealth	1122.14	1231.52	861	918
average_income	0.00	0.00	1.46	0.14	Individual Wealth	1122.14	1231.52	861	918
location_size2	-0.15	0.60	-0.24	0.81	Individual Wealth	1122.14	1231.52	861	918
location_size3	-0.76	0.63	-1.20	0.23	Individual Wealth	1122.14	1231.52	861	918
location_size4	-0.86	0.64	-1.34	0.18	Individual Wealth	1122.14	1231.52	861	918
location_size5	-0.01	0.62	-0.01	0.99	Individual Wealth	1122.14	1231.52	861	918
famil_numb	0.34	0.15	2.27	0.02	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:sex2	-0.42	0.38	-1.11	0.27	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:age	-0.01	0.02	-0.73	0.46	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:educ2	2.13	0.92	2.33	0.02	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:educ3	2.07	1.13	1.83	0.07	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:educ4	2.35	0.84	2.79	0.01	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:educ5	16.24	710.58	0.02	0.98	Individual Wealth	1122.14	1231.52	861	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:educ6	2.93	0.89	3.29	0.00	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl2	0.34	1.13	0.31	0.76	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl3	-0.04	0.93	-0.04	0.97	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl4	0.38	1.03	0.37	0.71	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl5	0.81	0.96	0.84	0.40	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl6					Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl7	0.38	1.03	0.37	0.71	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl8	-0.99	1.39	-0.72	0.47	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl9	-1.56	1.78	-0.87	0.38	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl10	1.71	1.53	1.12	0.26	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:empl11	0.42	2.03	0.21	0.84	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:marr_stat2	1.94	1.11	1.75	0.08	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:marr_stat3	-0.17	0.58	-0.30	0.77	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:marr_stat4	1.33	0.61	2.18	0.03	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:marr_stat5	-1.85	1226.17	-0.00	1.00	Individual Wealth	1122.14	1231.52	861	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:marr_stat6	-0.42	0.62	-0.68	0.50	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:average_income	-0.00	0.00	-0.78	0.44	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:location_size2	0.26	0.73	0.35	0.72	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:location_size3	0.77	0.76	1.02	0.31	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:location_size4	1.12	0.77	1.45	0.15	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:location_size5	0.32	0.75	0.43	0.67	Individual Wealth	1122.14	1231.52	861	918
indivwealth_d1:famil_numb	-0.29	0.17	-1.71	0.09	Individual Wealth	1122.14	1231.52	861	918

Table 2: GLM model: UR voters vs non-voters

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-3.58	0.90	-3.98	0.00	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1	2.78	1.86	1.49	0.14	Infrastructural development	1241.76	1497.03	1051	1109
sex2	0.54	0.19	2.79	0.01	Infrastructural development	1241.76	1497.03	1051	1109
age	0.04	0.01	4.82	0.00	Infrastructural development	1241.76	1497.03	1051	1109
educ2	-0.78	0.56	-1.38	0.17	Infrastructural development	1241.76	1497.03	1051	1109
educ3	-0.74	0.69	-1.08	0.28	Infrastructural development	1241.76	1497.03	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ4	-0.26	0.53	-0.50	0.62	Infrastructural development	1241.76	1497.03	1051	1109
educ5	-1.34	0.85	-1.58	0.12	Infrastructural development	1241.76	1497.03	1051	1109
educ6	-0.27	0.56	-0.49	0.63	Infrastructural development	1241.76	1497.03	1051	1109
empl2	-0.39	0.52	-0.74	0.46	Infrastructural development	1241.76	1497.03	1051	1109
empl3	0.06	0.42	0.14	0.89	Infrastructural development	1241.76	1497.03	1051	1109
empl4	-0.34	0.45	-0.76	0.45	Infrastructural development	1241.76	1497.03	1051	1109
empl5	-0.31	0.41	-0.75	0.46	Infrastructural development	1241.76	1497.03	1051	1109
empl6	-0.98	0.86	-1.14	0.25	Infrastructural development	1241.76	1497.03	1051	1109
empl7	0.62	0.47	1.33	0.18	Infrastructural development	1241.76	1497.03	1051	1109
empl8	0.23	0.57	0.40	0.69	Infrastructural development	1241.76	1497.03	1051	1109
empl9	0.34	0.52	0.65	0.52	Infrastructural development	1241.76	1497.03	1051	1109
empl10	0.22	0.55	0.39	0.70	Infrastructural development	1241.76	1497.03	1051	1109
empl11	-0.92	1.03	-0.90	0.37	Infrastructural development	1241.76	1497.03	1051	1109
marr_stat2	-0.43	0.42	-1.02	0.31	Infrastructural development	1241.76	1497.03	1051	1109
marr_stat3	-0.35	0.34	-1.04	0.30	Infrastructural development	1241.76	1497.03	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat4	-0.10	0.28	-0.37	0.71	Infrastructural development	1241.76	1497.03	1051	1109
marr_stat5	-16.86	1209.25	-0.01	0.99	Infrastructural development	1241.76	1497.03	1051	1109
marr_stat6	-0.40	0.26	-1.55	0.12	Infrastructural development	1241.76	1497.03	1051	1109
average_income	0.00	0.00	2.09	0.04	Infrastructural development	1241.76	1497.03	1051	1109
location_size2	1.33	0.30	4.43	0.00	Infrastructural development	1241.76	1497.03	1051	1109
location_size3	1.44	0.33	4.32	0.00	Infrastructural development	1241.76	1497.03	1051	1109
location_size4	1.23	0.31	3.91	0.00	Infrastructural development	1241.76	1497.03	1051	1109
location_size5	1.33	0.32	4.15	0.00	Infrastructural development	1241.76	1497.03	1051	1109
famil_numb	0.09	0.08	1.14	0.25	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:sex2	0.08	0.37	0.21	0.83	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:age	-0.00	0.02	-0.01	1.00	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:educ2	-1.82	1.36	-1.34	0.18	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:educ3	-1.57	1.53	-1.03	0.30	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:educ4	-2.35	1.32	-1.79	0.07	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:educ5	-17.12	827.84	-0.02	0.98	Infrastructural development	1241.76	1497.03	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:educ6	-2.14	1.36	-1.58	0.11	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl2	0.18	0.93	0.19	0.85	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl3	-0.67	0.77	-0.88	0.38	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl4	-0.09	0.83	-0.10	0.92	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl5	-0.28	0.78	-0.36	0.72	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl6	-14.96	785.90	-0.02	0.98	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl7	-0.87	0.88	-0.99	0.32	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl8	0.32	1.05	0.30	0.76	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl9	-0.74	1.06	-0.70	0.48	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl10	-0.68	1.09	-0.62	0.53	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:empl11	-0.64	1.69	-0.38	0.71	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:marr_stat2	0.33	0.84	0.39	0.70	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:marr_stat3	-0.13	0.60	-0.22	0.82	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:marr_stat4	-0.35	0.56	-0.64	0.53	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:marr_stat5	-0.43	2038.31	-0.00	1.00	Infrastructural development	1241.76	1497.03	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:marr_stat6	0.26	0.51	0.51	0.61	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:average_income	0.00	0.00	1.18	0.24	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:location_size2	-1.10	0.58	-1.89	0.06	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:location_size3	-1.24	0.63	-1.96	0.05	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:location_size4	-0.98	0.59	-1.66	0.10	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:location_size5	-0.80	0.59	-1.34	0.18	Infrastructural development	1241.76	1497.03	1051	1109
infrastr_d1:famil_numb	0.18	0.16	1.13	0.26	Infrastructural development	1241.76	1497.03	1051	1109
(Intercept)	-2.68	0.75	-3.57	0.00	Social Support	1310.82	1535.93	1051	1109
socialsup_d1	-1.15	1.90	-0.60	0.55	Social Support	1310.82	1535.93	1051	1109
sex2	0.35	0.17	2.06	0.04	Social Support	1310.82	1535.93	1051	1109
age	0.03	0.01	4.21	0.00	Social Support	1310.82	1535.93	1051	1109
educ2	-0.45	0.42	-1.09	0.27	Social Support	1310.82	1535.93	1051	1109
educ3	-0.25	0.54	-0.47	0.64	Social Support	1310.82	1535.93	1051	1109
educ4	-0.04	0.38	-0.12	0.91	Social Support	1310.82	1535.93	1051	1109
educ5	-1.67	0.69	-2.43	0.02	Social Support	1310.82	1535.93	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	0.15	0.39	0.39	0.70	Social Support	1310.82	1535.93	1051	1109
empl2	0.63	0.46	1.36	0.17	Social Support	1310.82	1535.93	1051	1109
empl3	-0.23	0.36	-0.63	0.53	Social Support	1310.82	1535.93	1051	1109
empl4	-0.09	0.40	-0.22	0.83	Social Support	1310.82	1535.93	1051	1109
empl5	-0.56	0.34	-1.63	0.10	Social Support	1310.82	1535.93	1051	1109
empl6	-0.64	0.50	-1.29	0.20	Social Support	1310.82	1535.93	1051	1109
empl7	0.29	0.43	0.68	0.50	Social Support	1310.82	1535.93	1051	1109
empl8	0.85	0.57	1.49	0.14	Social Support	1310.82	1535.93	1051	1109
empl9	-0.79	0.50	-1.59	0.11	Social Support	1310.82	1535.93	1051	1109
empl10	0.01	0.44	0.02	0.99	Social Support	1310.82	1535.93	1051	1109
empl11	0.25	0.49	0.51	0.61	Social Support	1310.82	1535.93	1051	1109
marr_stat2	-0.93	0.45	-2.08	0.04	Social Support	1310.82	1535.93	1051	1109
marr_stat3	-0.43	0.36	-1.21	0.23	Social Support	1310.82	1535.93	1051	1109
marr_stat4	0.06	0.25	0.23	0.82	Social Support	1310.82	1535.93	1051	1109
marr_stat5	-17.24	1101.64	-0.02	0.99	Social Support	1310.82	1535.93	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat6	-0.11	0.22	-0.51	0.61	Social Support	1310.82	1535.93	1051	1109
average_income	-0.00	0.00	-0.02	0.98	Social Support	1310.82	1535.93	1051	1109
location_size2	0.62	0.28	2.19	0.03	Social Support	1310.82	1535.93	1051	1109
location_size3	0.92	0.30	3.08	0.00	Social Support	1310.82	1535.93	1051	1109
location_size4	0.69	0.29	2.38	0.02	Social Support	1310.82	1535.93	1051	1109
location_size5	1.08	0.29	3.72	0.00	Social Support	1310.82	1535.93	1051	1109
famil_numb	0.18	0.07	2.43	0.02	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:sex2	0.79	0.44	1.78	0.08	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:age	0.01	0.02	0.27	0.79	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:educ2	0.39	1.09	0.36	0.72	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:educ3	-0.91	1.31	-0.69	0.49	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:educ4	-0.44	0.98	-0.45	0.65	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:educ5	-14.49	879.26	-0.02	0.99	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:educ6	-0.26	1.00	-0.25	0.80	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl2	-0.75	1.18	-0.64	0.53	Social Support	1310.82	1535.93	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:empl3	-0.11	0.88	-0.12	0.90	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl4	-0.30	0.98	-0.31	0.76	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl5	-0.09	0.85	-0.10	0.92	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl6	-15.03	601.97	-0.02	0.98	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl7	-0.39	1.03	-0.38	0.70	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl8	-2.30	1.54	-1.49	0.14	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl9	0.64	1.14	0.56	0.57	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl10	-0.76	1.09	-0.69	0.49	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:empl11	-2.41	1.52	-1.59	0.11	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:marr_stat2	1.42	1.01	1.41	0.16	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:marr_stat3	0.05	0.87	0.06	0.95	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:marr_stat4	-0.52	0.61	-0.85	0.40	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:marr_stat5	0.45	2690.59	0.00	1.00	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:marr_stat6	-0.80	0.59	-1.35	0.18	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:average_income	0.00	0.00	1.71	0.09	Social Support	1310.82	1535.93	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:location_size2	-0.08	0.68	-0.12	0.90	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:location_size3	0.12	0.81	0.15	0.88	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:location_size4	0.31	0.74	0.42	0.68	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:location_size5	0.08	0.73	0.11	0.91	Social Support	1310.82	1535.93	1051	1109
socialsup_d1:famil_numb	0.10	0.15	0.69	0.49	Social Support	1310.82	1535.93	1051	1109
(Intercept)	-3.05	0.81	-3.75	0.00	Economic Development	1306.93	1543.54	1051	1109
econdev_d1	0.17	1.95	0.09	0.93	Economic Development	1306.93	1543.54	1051	1109
sex2	0.36	0.18	2.03	0.04	Economic Development	1306.93	1543.54	1051	1109
age	0.04	0.01	5.41	0.00	Economic Development	1306.93	1543.54	1051	1109
educ2	0.07	0.44	0.15	0.88	Economic Development	1306.93	1543.54	1051	1109
educ3	0.07	0.57	0.12	0.90	Economic Development	1306.93	1543.54	1051	1109
educ4	-0.07	0.42	-0.17	0.87	Economic Development	1306.93	1543.54	1051	1109
educ5	0.91	0.86	1.05	0.29	Economic Development	1306.93	1543.54	1051	1109
educ6	-0.46	0.44	-1.03	0.30	Economic Development	1306.93	1543.54	1051	1109
empl2	1.25	0.52	2.41	0.02	Economic Development	1306.93	1543.54	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl3	0.82	0.42	1.96	0.05	Economic Development	1306.93	1543.54	1051	1109
empl4	0.52	0.45	1.17	0.24	Economic Development	1306.93	1543.54	1051	1109
empl5	0.33	0.40	0.83	0.41	Economic Development	1306.93	1543.54	1051	1109
empl6	-0.46	0.72	-0.64	0.52	Economic Development	1306.93	1543.54	1051	1109
empl7	1.18	0.46	2.56	0.01	Economic Development	1306.93	1543.54	1051	1109
empl8	0.42	0.59	0.71	0.48	Economic Development	1306.93	1543.54	1051	1109
empl9	0.66	0.51	1.30	0.19	Economic Development	1306.93	1543.54	1051	1109
empl10	1.16	0.55	2.12	0.03	Economic Development	1306.93	1543.54	1051	1109
empl11	0.31	0.60	0.52	0.61	Economic Development	1306.93	1543.54	1051	1109
marr_stat2	-0.33	0.39	-0.85	0.40	Economic Development	1306.93	1543.54	1051	1109
marr_stat3	-0.17	0.31	-0.56	0.58	Economic Development	1306.93	1543.54	1051	1109
marr_stat4	0.39	0.26	1.49	0.14	Economic Development	1306.93	1543.54	1051	1109
marr_stat5	-15.12	760.98	-0.02	0.98	Economic Development	1306.93	1543.54	1051	1109
marr_stat6	0.05	0.22	0.21	0.83	Economic Development	1306.93	1543.54	1051	1109
average_income	0.00	0.00	0.78	0.44	Economic Development	1306.93	1543.54	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size2	-0.36	0.31	-1.15	0.25	Economic Development	1306.93	1543.54	1051	1109
location_size3	-0.78	0.31	-2.48	0.01	Economic Development	1306.93	1543.54	1051	1109
location_size4	-0.31	0.32	-0.97	0.33	Economic Development	1306.93	1543.54	1051	1109
location_size5	-0.42	0.33	-1.27	0.21	Economic Development	1306.93	1543.54	1051	1109
famil_numb	0.21	0.07	3.11	0.00	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:sex2	-0.01	0.45	-0.01	0.99	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:age	-0.00	0.02	-0.03	0.97	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:educ2	-1.43	1.02	-1.39	0.16	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:educ3	-0.06	1.37	-0.04	0.97	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:educ4	-0.70	0.95	-0.74	0.46	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:educ5	-16.82	674.45	-0.02	0.98	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:educ6	-0.78	1.03	-0.76	0.45	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl2	-0.28	1.42	-0.20	0.84	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl3	-0.41	1.01	-0.40	0.69	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl4	-0.93	1.10	-0.84	0.40	Economic Development	1306.93	1543.54	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:empl5	-0.84	1.00	-0.84	0.40	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl6	-0.12	1.66	-0.07	0.94	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl7	-0.63	1.15	-0.55	0.59	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl8	-0.05	1.38	-0.03	0.97	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl9	-0.54	1.20	-0.45	0.65	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl10	-1.44	1.18	-1.22	0.22	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:empl11	-2.29	1.54	-1.49	0.14	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:marr_stat2	-0.26	0.91	-0.29	0.77	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:marr_stat3	0.42	0.70	0.61	0.54	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:marr_stat4	-0.69	0.65	-1.05	0.29	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:marr_stat5	-0.01	1281.51	-0.00	1.00	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:marr_stat6	-0.38	0.57	-0.66	0.51	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:average_income	0.00	0.00	0.75	0.45	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:location_size2	0.89	0.75	1.18	0.24	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:location_size3	1.70	0.76	2.25	0.02	Economic Development	1306.93	1543.54	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:location_size4	1.40	0.73	1.93	0.05	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:location_size5	1.84	0.75	2.46	0.01	Economic Development	1306.93	1543.54	1051	1109
econdev_d1:famil_numb	-0.05	0.18	-0.28	0.78	Economic Development	1306.93	1543.54	1051	1109
(Intercept)	-11.47	4.01	-2.86	0.00	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1	8.69	4.08	2.13	0.03	Personal Connections	1254.73	1527.94	1052	1109
sex2	0.50	0.76	0.65	0.51	Personal Connections	1254.73	1527.94	1052	1109
age	0.06	0.04	1.69	0.09	Personal Connections	1254.73	1527.94	1052	1109
educ2	0.23	2.39	0.10	0.92	Personal Connections	1254.73	1527.94	1052	1109
educ3	1.25	2.93	0.43	0.67	Personal Connections	1254.73	1527.94	1052	1109
educ4	0.60	2.33	0.26	0.80	Personal Connections	1254.73	1527.94	1052	1109
educ5	-15.20	954.46	-0.02	0.99	Personal Connections	1254.73	1527.94	1052	1109
educ6	1.44	2.39	0.60	0.55	Personal Connections	1254.73	1527.94	1052	1109
empl2	0.09	2.34	0.04	0.97	Personal Connections	1254.73	1527.94	1052	1109
empl3	-0.59	1.55	-0.38	0.70	Personal Connections	1254.73	1527.94	1052	1109
empl4	-2.67	1.81	-1.47	0.14	Personal Connections	1254.73	1527.94	1052	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl5	-2.80	1.67	-1.68	0.09	Personal Connections	1254.73	1527.94	1052	1109
empl6	-5.63	3.78	-1.49	0.14	Personal Connections	1254.73	1527.94	1052	1109
empl7	-0.20	1.94	-0.10	0.92	Personal Connections	1254.73	1527.94	1052	1109
empl8	-18.27	792.73	-0.02	0.98	Personal Connections	1254.73	1527.94	1052	1109
empl9	-1.14	2.00	-0.57	0.57	Personal Connections	1254.73	1527.94	1052	1109
empl10	-0.88	1.97	-0.45	0.66	Personal Connections	1254.73	1527.94	1052	1109
empl11	-7.71	3.91	-1.97	0.05	Personal Connections	1254.73	1527.94	1052	1109
marr_stat2	0.75	1.75	0.43	0.67	Personal Connections	1254.73	1527.94	1052	1109
marr_stat3	1.83	1.31	1.40	0.16	Personal Connections	1254.73	1527.94	1052	1109
marr_stat4	2.93	1.27	2.32	0.02	Personal Connections	1254.73	1527.94	1052	1109
marr_stat5	-15.77	652.39	-0.02	0.98	Personal Connections	1254.73	1527.94	1052	1109
marr_stat6	2.66	1.20	2.21	0.03	Personal Connections	1254.73	1527.94	1052	1109
average_income	0.00	0.00	2.80	0.01	Personal Connections	1254.73	1527.94	1052	1109
location_size2	1.77	1.23	1.44	0.15	Personal Connections	1254.73	1527.94	1052	1109
location_size3	0.71	1.22	0.58	0.56	Personal Connections	1254.73	1527.94	1052	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size4	2.29	1.15	1.99	0.05	Personal Connections	1254.73	1527.94	1052	1109
location_size5	2.28	1.31	1.74	0.08	Personal Connections	1254.73	1527.94	1052	1109
famil_numb	1.58	0.48	3.30	0.00	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:sex2	0.05	0.78	0.06	0.95	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:age	-0.03	0.04	-0.77	0.44	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:educ2	-0.87	2.43	-0.36	0.72	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:educ3	-1.85	2.99	-0.62	0.54	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:educ4	-1.06	2.37	-0.45	0.65	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:educ5	14.78	954.46	0.02	0.99	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:educ6	-2.00	2.43	-0.82	0.41	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl2	0.40	2.39	0.17	0.87	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl3	0.93	1.60	0.58	0.56	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl4	2.91	1.86	1.57	0.12	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl5	2.90	1.71	1.70	0.09	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl6	4.40	3.86	1.14	0.25	Personal Connections	1254.73	1527.94	1052	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:empl7	0.98	1.99	0.49	0.62	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl8	19.09	792.73	0.02	0.98	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl9	1.50	2.07	0.72	0.47	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl10	1.28	2.03	0.63	0.53	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:empl11	7.17	3.98	1.80	0.07	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:marr_stat2	-1.33	1.79	-0.74	0.46	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:marr_stat3	-2.19	1.34	-1.63	0.10	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:marr_stat4	-3.12	1.29	-2.41	0.02	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:marr_stat5					Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:marr_stat6	-3.09	1.22	-2.52	0.01	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:average_income	-0.00	0.00	-2.47	0.01	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:location_size2	-1.26	1.27	-0.99	0.32	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:location_size3	-0.14	1.26	-0.11	0.91	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:location_size4	-1.58	1.19	-1.32	0.19	Personal Connections	1254.73	1527.94	1052	1109
personconnect_d1:location_size5	-1.59	1.35	-1.18	0.24	Personal Connections	1254.73	1527.94	1052	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:famil_numb	-1.44	0.48	-2.98	0.00	Personal Connections	1254.73	1527.94	1052	1109
(Intercept)	-1.10	1.42	-0.78	0.44	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth.d1	-3.13	1.68	-1.86	0.06	Individual Wealth	1257.59	1563.22	1051	1109
sex2	0.96	0.29	3.32	0.00	Individual Wealth	1257.59	1563.22	1051	1109
age	0.06	0.01	4.42	0.00	Individual Wealth	1257.59	1563.22	1051	1109
educ2	-3.41	0.89	-3.81	0.00	Individual Wealth	1257.59	1563.22	1051	1109
educ3	-2.24	1.08	-2.08	0.04	Individual Wealth	1257.59	1563.22	1051	1109
educ4	-3.57	0.85	-4.17	0.00	Individual Wealth	1257.59	1563.22	1051	1109
educ5	-19.13	724.91	-0.03	0.98	Individual Wealth	1257.59	1563.22	1051	1109
educ6	-3.55	0.89	-4.01	0.00	Individual Wealth	1257.59	1563.22	1051	1109
empl2	0.96	0.79	1.20	0.23	Individual Wealth	1257.59	1563.22	1051	1109
empl3	1.31	0.63	2.06	0.04	Individual Wealth	1257.59	1563.22	1051	1109
empl4	1.18	0.72	1.64	0.10	Individual Wealth	1257.59	1563.22	1051	1109
empl5	0.33	0.66	0.50	0.62	Individual Wealth	1257.59	1563.22	1051	1109
empl6	-13.89	606.08	-0.02	0.98	Individual Wealth	1257.59	1563.22	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl7	0.57	0.71	0.81	0.42	Individual Wealth	1257.59	1563.22	1051	1109
empl8	2.00	0.89	2.25	0.02	Individual Wealth	1257.59	1563.22	1051	1109
empl9	0.88	0.89	0.99	0.32	Individual Wealth	1257.59	1563.22	1051	1109
empl10	-0.25	0.87	-0.29	0.77	Individual Wealth	1257.59	1563.22	1051	1109
empl11	-1.29	1.65	-0.79	0.43	Individual Wealth	1257.59	1563.22	1051	1109
marr_stat2	0.17	0.72	0.24	0.81	Individual Wealth	1257.59	1563.22	1051	1109
marr_stat3	-0.58	0.45	-1.27	0.20	Individual Wealth	1257.59	1563.22	1051	1109
marr_stat4	-1.24	0.51	-2.45	0.01	Individual Wealth	1257.59	1563.22	1051	1109
marr_stat5	-15.80	1723.57	-0.01	0.99	Individual Wealth	1257.59	1563.22	1051	1109
marr_stat6	-0.60	0.42	-1.43	0.15	Individual Wealth	1257.59	1563.22	1051	1109
average_income	0.00	0.00	1.56	0.12	Individual Wealth	1257.59	1563.22	1051	1109
location_size2	-0.50	0.52	-0.97	0.33	Individual Wealth	1257.59	1563.22	1051	1109
location_size3	-0.41	0.55	-0.75	0.45	Individual Wealth	1257.59	1563.22	1051	1109
location_size4	-0.98	0.53	-1.86	0.06	Individual Wealth	1257.59	1563.22	1051	1109
location_size5	0.02	0.52	0.03	0.97	Individual Wealth	1257.59	1563.22	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.16	0.12	1.31	0.19	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:sex2	-0.67	0.35	-1.91	0.06	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:age	-0.03	0.02	-1.62	0.11	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:educ2	3.80	1.04	3.65	0.00	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:educ3	2.90	1.28	2.27	0.02	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:educ4	4.27	0.99	4.29	0.00	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:educ5	19.49	724.91	0.03	0.98	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:educ6	4.13	1.03	4.00	0.00	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl2	-0.35	0.95	-0.37	0.71	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl3	-0.94	0.76	-1.24	0.22	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl4	-1.00	0.86	-1.17	0.24	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl5	-0.44	0.78	-0.56	0.57	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl6	13.25	606.08	0.02	0.98	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl7	0.35	0.86	0.41	0.68	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl8	-1.54	1.08	-1.42	0.15	Individual Wealth	1257.59	1563.22	1051	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:empl9	-0.67	1.04	-0.65	0.52	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl10	1.04	1.02	1.02	0.31	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:empl11	0.99	1.81	0.55	0.58	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:marr_stat2	-0.79	0.84	-0.94	0.35	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:marr_stat3	0.41	0.57	0.72	0.47	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:marr_stat4	1.67	0.59	2.82	0.00	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:marr_stat5	-0.31	2445.38	-0.00	1.00	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:marr_stat6	0.33	0.48	0.68	0.50	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:average_income	-0.00	0.00	-0.26	0.79	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:location_size2	1.37	0.64	2.16	0.03	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:location_size3	1.13	0.66	1.69	0.09	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:location_size4	2.08	0.65	3.22	0.00	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:location_size5	0.90	0.64	1.40	0.16	Individual Wealth	1257.59	1563.22	1051	1109
indivwealth_d1:famil_numb	-0.01	0.15	-0.04	0.97	Individual Wealth	1257.59	1563.22	1051	1109

Table 3: GLM model: UR core vs swing voters

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-4.24	1.52	-2.78	0.01	Infrastructural development	557.39	640.55	450	504
infrastr_d1	3.59	2.77	1.29	0.20	Infrastructural development	557.39	640.55	450	504
sex2	0.22	0.30	0.72	0.47	Infrastructural development	557.39	640.55	450	504
age	-0.00	0.01	-0.24	0.81	Infrastructural development	557.39	640.55	450	504
educ2	1.26	0.76	1.66	0.10	Infrastructural development	557.39	640.55	450	504
educ3	1.78	1.03	1.73	0.09	Infrastructural development	557.39	640.55	450	504
educ4	0.75	0.71	1.06	0.29	Infrastructural development	557.39	640.55	450	504
educ5	1.29	1.36	0.95	0.34	Infrastructural development	557.39	640.55	450	504
educ6	1.23	0.74	1.66	0.10	Infrastructural development	557.39	640.55	450	504
empl2	0.70	1.08	0.65	0.52	Infrastructural development	557.39	640.55	450	504
empl3	1.54	0.90	1.71	0.09	Infrastructural development	557.39	640.55	450	504
empl4	2.06	0.95	2.16	0.03	Infrastructural development	557.39	640.55	450	504
empl5	1.73	0.92	1.89	0.06	Infrastructural development	557.39	640.55	450	504
empl6	-15.40	2530.87	-0.01	1.00	Infrastructural development	557.39	640.55	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl7	2.28	0.95	2.41	0.02	Infrastructure development	557.39	640.55	450	504
empl8	1.82	1.04	1.74	0.08	Infrastructure development	557.39	640.55	450	504
empl9	1.09	1.01	1.08	0.28	Infrastructure development	557.39	640.55	450	504
empl10	0.69	1.16	0.60	0.55	Infrastructure development	557.39	640.55	450	504
empl11	0.67	2.33	0.29	0.77	Infrastructure development	557.39	640.55	450	504
marr_stat2	-0.80	0.92	-0.87	0.39	Infrastructure development	557.39	640.55	450	504
marr_stat3	0.04	0.37	0.11	0.91	Infrastructure development	557.39	640.55	450	504
marr_stat4	-0.69	0.42	-1.65	0.10	Infrastructure development	557.39	640.55	450	504
marr_stat6	-0.35	0.45	-0.78	0.44	Infrastructure development	557.39	640.55	450	504
average_income	0.00	0.00	1.55	0.12	Infrastructure development	557.39	640.55	450	504
location_size2	1.14	0.52	2.21	0.03	Infrastructure development	557.39	640.55	450	504
location_size3	0.99	0.55	1.80	0.07	Infrastructure development	557.39	640.55	450	504
location_size4	0.78	0.55	1.43	0.15	Infrastructure development	557.39	640.55	450	504
location_size5	1.22	0.53	2.31	0.02	Infrastructure development	557.39	640.55	450	504
famil numb	0.00	0.13	0.04	0.97	Infrastructure development	557.39	640.55	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:sex2	0.37	0.73	0.51	0.61	Infrastructure development	557.39	640.55	450	504
infrastr_d1:age	-0.03	0.03	-1.10	0.27	Infrastructure development	557.39	640.55	450	504
infrastr_d1:educ2	-0.14	1.51	-0.09	0.93	Infrastructure development	557.39	640.55	450	504
infrastr_d1:educ3	-17.68	1651.00	-0.01	0.99	Infrastructure development	557.39	640.55	450	504
infrastr_d1:educ4	0.13	1.41	0.10	0.92	Infrastructure development	557.39	640.55	450	504
infrastr_d1:educ5					Infrastructure development	557.39	640.55	450	504
infrastr_d1:educ6	0.60	1.62	0.37	0.71	Infrastructure development	557.39	640.55	450	504
infrastr_d1:empl2	-19.27	1220.39	-0.02	0.99	Infrastructure development	557.39	640.55	450	504
infrastr_d1:empl3	-3.35	1.43	-2.35	0.02	Infrastructure development	557.39	640.55	450	504
infrastr_d1:empl4	-3.81	1.59	-2.40	0.02	Infrastructure development	557.39	640.55	450	504
infrastr_d1:empl5	-2.08	1.47	-1.42	0.16	Infrastructure development	557.39	640.55	450	504
infrastr_d1:empl6					Infrastructure development	557.39	640.55	450	504
infrastr_d1:empl7	-3.33	1.62	-2.06	0.04	Infrastructure development	557.39	640.55	450	504
infrastr_d1:empl8	-1.23	1.74	-0.71	0.48	Infrastructure development	557.39	640.55	450	504
infrastr_d1:empl9	-3.62	1.89	-1.91	0.06	Infrastructure development	557.39	640.55	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:empl10	-18.43	1712.43	-0.01	0.99	Infrastructural development	557.39	640.55	450	504
infrastr_d1:empl11	-19.56	4072.82	-0.00	1.00	Infrastructural development	557.39	640.55	450	504
infrastr_d1:marr_stat2	-0.22	1.68	-0.13	0.90	Infrastructural development	557.39	640.55	450	504
infrastr_d1:marr_stat3	-0.08	0.89	-0.09	0.93	Infrastructural development	557.39	640.55	450	504
infrastr_d1:marr_stat4	0.37	0.94	0.39	0.70	Infrastructural development	557.39	640.55	450	504
infrastr_d1:marr_stat6	-1.40	1.05	-1.33	0.19	Infrastructural development	557.39	640.55	450	504
infrastr_d1:average_income	0.00	0.00	0.28	0.78	Infrastructural development	557.39	640.55	450	504
infrastr_d1:location_size2	-0.71	1.14	-0.62	0.54	Infrastructural development	557.39	640.55	450	504
infrastr_d1:location_size3	1.25	1.23	1.02	0.31	Infrastructural development	557.39	640.55	450	504
infrastr_d1:location_size4	0.99	1.17	0.84	0.40	Infrastructural development	557.39	640.55	450	504
infrastr_d1:location_size5	-0.12	1.15	-0.10	0.92	Infrastructural development	557.39	640.55	450	504
infrastr_d1:famil_numb	-0.06	0.26	-0.23	0.82	Infrastructural development	557.39	640.55	450	504
(Intercept)	-2.43	1.26	-1.92	0.06	Social Support	540.10	645.86	450	504
socialsup_d1	-8.15	1057.77	-0.01	0.99	Social Support	540.10	645.86	450	504
sex2	0.02	0.29	0.08	0.94	Social Support	540.10	645.86	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
age	0.00	0.01	0.02	0.98	Social Support	540.10	645.86	450	504
educ2	0.60	0.70	0.87	0.39	Social Support	540.10	645.86	450	504
educ3	0.93	0.86	1.08	0.28	Social Support	540.10	645.86	450	504
educ4	0.17	0.62	0.27	0.79	Social Support	540.10	645.86	450	504
educ5	0.67	1.30	0.52	0.61	Social Support	540.10	645.86	450	504
educ6	1.19	0.65	1.82	0.07	Social Support	540.10	645.86	450	504
empl2	-1.56	0.74	-2.10	0.04	Social Support	540.10	645.86	450	504
empl3	0.01	0.57	0.02	0.98	Social Support	540.10	645.86	450	504
empl4	0.14	0.64	0.21	0.83	Social Support	540.10	645.86	450	504
empl5	0.31	0.55	0.57	0.57	Social Support	540.10	645.86	450	504
empl6	-16.09	1096.42	-0.01	0.99	Social Support	540.10	645.86	450	504
empl7	0.45	0.65	0.69	0.49	Social Support	540.10	645.86	450	504
empl8	1.41	0.79	1.80	0.07	Social Support	540.10	645.86	450	504
empl9	-1.01	0.86	-1.17	0.24	Social Support	540.10	645.86	450	504
empl10	-0.82	0.73	-1.12	0.26	Social Support	540.10	645.86	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-3.45	1.42	-2.44	0.02	Social Support	540.10	645.86	450	504
marr_stat2	-0.61	0.90	-0.67	0.50	Social Support	540.10	645.86	450	504
marr_stat3	-0.54	0.48	-1.12	0.26	Social Support	540.10	645.86	450	504
marr_stat4	-0.48	0.38	-1.25	0.21	Social Support	540.10	645.86	450	504
marr_stat6	-0.89	0.42	-2.11	0.04	Social Support	540.10	645.86	450	504
average_income	0.00	0.00	1.50	0.13	Social Support	540.10	645.86	450	504
location_size2	1.00	0.50	2.01	0.05	Social Support	540.10	645.86	450	504
location_size3	1.68	0.51	3.30	0.00	Social Support	540.10	645.86	450	504
location_size4	1.45	0.52	2.82	0.01	Social Support	540.10	645.86	450	504
location_size5	1.27	0.51	2.50	0.01	Social Support	540.10	645.86	450	504
famil_numb	0.06	0.12	0.54	0.59	Social Support	540.10	645.86	450	504
socialsup_d1:sex2	0.26	0.97	0.27	0.79	Social Support	540.10	645.86	450	504
socialsup_d1:age	-0.03	0.05	-0.55	0.58	Social Support	540.10	645.86	450	504
socialsup_d1:educ2	-3.05	2.42	-1.26	0.21	Social Support	540.10	645.86	450	504
socialsup_d1:educ3	-2.70	2.77	-0.98	0.33	Social Support	540.10	645.86	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:educ4	-4.03	2.34	-1.72	0.09	Social Support	540.10	645.86	450	504
socialsup_d1:educ5					Social Support	540.10	645.86	450	504
socialsup_d1:educ6	-3.31	2.17	-1.52	0.13	Social Support	540.10	645.86	450	504
socialsup_d1:empl2	1.31	1659.49	0.00	1.00	Social Support	540.10	645.86	450	504
socialsup_d1:empl3	15.61	1057.77	0.01	0.99	Social Support	540.10	645.86	450	504
socialsup_d1:empl4	16.07	1057.77	0.02	0.99	Social Support	540.10	645.86	450	504
socialsup_d1:empl5	14.78	1057.77	0.01	0.99	Social Support	540.10	645.86	450	504
socialsup_d1:empl6					Social Support	540.10	645.86	450	504
socialsup_d1:empl7	15.96	1057.77	0.02	0.99	Social Support	540.10	645.86	450	504
socialsup_d1:empl8	-4.19	2786.36	-0.00	1.00	Social Support	540.10	645.86	450	504
socialsup_d1:empl9	13.99	1057.77	0.01	0.99	Social Support	540.10	645.86	450	504
socialsup_d1:empl10	16.84	1057.77	0.02	0.99	Social Support	540.10	645.86	450	504
socialsup_d1:empl11	5.65	2786.36	0.00	1.00	Social Support	540.10	645.86	450	504
socialsup_d1:marr_stat2	-15.13	1423.49	-0.01	0.99	Social Support	540.10	645.86	450	504
socialsup_d1:marr_stat3	2.00	1.74	1.15	0.25	Social Support	540.10	645.86	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:marr_stat4	1.79	1.37	1.31	0.19	Social Support	540.10	645.86	450	504
socialsup_d1:marr_stat6	-0.72	1.55	-0.47	0.64	Social Support	540.10	645.86	450	504
socialsup_d1:average.income	-0.00	0.00	-0.93	0.35	Social Support	540.10	645.86	450	504
socialsup_d1:location_size2	-1.04	1.47	-0.71	0.48	Social Support	540.10	645.86	450	504
socialsup_d1:location_size3	-1.33	1.83	-0.72	0.47	Social Support	540.10	645.86	450	504
socialsup_d1:location_size4	-4.30	2.09	-2.06	0.04	Social Support	540.10	645.86	450	504
socialsup_d1:location_size5	-1.66	1.58	-1.05	0.29	Social Support	540.10	645.86	450	504
socialsup_d1:famil_numb	-0.32	0.39	-0.84	0.40	Social Support	540.10	645.86	450	504
(Intercept)	-3.27	1.34	-2.43	0.02	Economic Development	567.29	662.61	449	504
econdev_d1	-1.31	3.32	-0.40	0.69	Economic Development	567.29	662.61	449	504
sex2	-0.34	0.29	-1.20	0.23	Economic Development	567.29	662.61	449	504
age	0.03	0.01	2.41	0.02	Economic Development	567.29	662.61	449	504
educ2	-0.02	0.64	-0.04	0.97	Economic Development	567.29	662.61	449	504
educ3	-0.37	0.78	-0.47	0.64	Economic Development	567.29	662.61	449	504
educ4	-0.11	0.61	-0.17	0.86	Economic Development	567.29	662.61	449	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ5	0.23	1.21	0.19	0.85	Economic Development	567.29	662.61	449	504
educ6	1.12	0.66	1.70	0.09	Economic Development	567.29	662.61	449	504
empl2	-2.25	1.08	-2.09	0.04	Economic Development	567.29	662.61	449	504
empl3	-0.25	0.71	-0.35	0.72	Economic Development	567.29	662.61	449	504
empl4	0.54	0.76	0.72	0.47	Economic Development	567.29	662.61	449	504
empl5	0.26	0.72	0.37	0.71	Economic Development	567.29	662.61	449	504
empl6	-14.34	823.90	-0.02	0.99	Economic Development	567.29	662.61	449	504
empl7	-0.27	0.76	-0.36	0.72	Economic Development	567.29	662.61	449	504
empl8	-0.92	0.98	-0.94	0.35	Economic Development	567.29	662.61	449	504
empl9	-0.83	0.91	-0.91	0.36	Economic Development	567.29	662.61	449	504
empl10	-1.05	0.99	-1.06	0.29	Economic Development	567.29	662.61	449	504
empl11	0.10	0.99	0.11	0.92	Economic Development	567.29	662.61	449	504
marr_stat2	-0.48	0.76	-0.63	0.53	Economic Development	567.29	662.61	449	504
marr_stat3	0.05	0.39	0.12	0.90	Economic Development	567.29	662.61	449	504
marr_stat4	-0.27	0.37	-0.73	0.47	Economic Development	567.29	662.61	449	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat6	-0.54	0.40	-1.35	0.18	Economic Development	567.29	662.61	449	504
average_income	0.00	0.00	0.99	0.32	Economic Development	567.29	662.61	449	504
location_size2	1.21	0.51	2.39	0.02	Economic Development	567.29	662.61	449	504
location_size3	1.37	0.53	2.59	0.01	Economic Development	567.29	662.61	449	504
location_size4	1.22	0.51	2.39	0.02	Economic Development	567.29	662.61	449	504
location_size5	1.16	0.53	2.19	0.03	Economic Development	567.29	662.61	449	504
famil_numb	0.17	0.11	1.49	0.14	Economic Development	567.29	662.61	449	504
econdev_d1:sex2	1.79	0.88	2.03	0.04	Economic Development	567.29	662.61	449	504
econdev_d1:age	-0.03	0.03	-0.96	0.34	Economic Development	567.29	662.61	449	504
econdev_d1:educ2	1.67	1.48	1.13	0.26	Economic Development	567.29	662.61	449	504
econdev_d1:educ3	2.39	2.23	1.07	0.29	Economic Development	567.29	662.61	449	504
econdev_d1:educ4	1.38	1.33	1.04	0.30	Economic Development	567.29	662.61	449	504
econdev_d1:educ5					Economic Development	567.29	662.61	449	504
econdev_d1:educ6	-0.67	1.54	-0.43	0.66	Economic Development	567.29	662.61	449	504
econdev_d1:empl2	1.56	2.77	0.56	0.57	Economic Development	567.29	662.61	449	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:empl3	-0.29	1.87	-0.16	0.88	Economic Development	567.29	662.61	449	504
econdev_d1:empl4	-3.45	2.39	-1.45	0.15	Economic Development	567.29	662.61	449	504
econdev_d1:empl5	0.54	1.93	0.28	0.78	Economic Development	567.29	662.61	449	504
econdev_d1:empl6	-1.53	1709.68	-0.00	1.00	Economic Development	567.29	662.61	449	504
econdev_d1:empl7	0.05	2.14	0.02	0.98	Economic Development	567.29	662.61	449	504
econdev_d1:empl8	1.77	2.51	0.71	0.48	Economic Development	567.29	662.61	449	504
econdev_d1:empl9	-0.38	2.22	-0.17	0.87	Economic Development	567.29	662.61	449	504
econdev_d1:empl10	2.23	2.20	1.01	0.31	Economic Development	567.29	662.61	449	504
econdev_d1:empl11	-22.23	1498.06	-0.01	0.99	Economic Development	567.29	662.61	449	504
econdev_d1:marr_stat2	-15.13	757.24	-0.02	0.98	Economic Development	567.29	662.61	449	504
econdev_d1:marr_stat3	0.60	0.89	0.68	0.50	Economic Development	567.29	662.61	449	504
econdev_d1:marr_stat4	0.96	1.06	0.91	0.36	Economic Development	567.29	662.61	449	504
econdev_d1:marr_stat6	-0.03	1.11	-0.02	0.98	Economic Development	567.29	662.61	449	504
econdev_d1:average_income	0.00	0.00	1.83	0.07	Economic Development	567.29	662.61	449	504
econdev_d1:location_size2	-0.91	1.30	-0.71	0.48	Economic Development	567.29	662.61	449	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:location_size3	-0.77	1.35	-0.57	0.57	Economic Development	567.29	662.61	449	504
econdev_d1:location_size4	0.46	1.37	0.34	0.74	Economic Development	567.29	662.61	449	504
econdev_d1:location_size5	0.06	1.24	0.05	0.96	Economic Development	567.29	662.61	449	504
econdev_d1:famil_numb	-0.13	0.29	-0.43	0.67	Economic Development	567.29	662.61	449	504
(Intercept)	-1.60	0.38	-4.21	0.00	Personal Connections	662.18	674.79	502	504
personconnect_d1	1.25	0.39	3.18	0.00	Personal Connections	662.18	674.79	502	504
(Intercept)	-6.89	2.54	-2.71	0.01	Individual Wealth	586.08	671.04	450	504
indivwealth_d1	4.94	2.91	1.70	0.09	Individual Wealth	586.08	671.04	450	504
sex2	1.49	0.57	2.61	0.01	Individual Wealth	586.08	671.04	450	504
age	0.00	0.02	0.02	0.98	Individual Wealth	586.08	671.04	450	504
educ2	0.10	0.98	0.10	0.92	Individual Wealth	586.08	671.04	450	504
educ3	-0.16	1.29	-0.13	0.90	Individual Wealth	586.08	671.04	450	504
educ4	-0.66	0.89	-0.74	0.46	Individual Wealth	586.08	671.04	450	504
educ5	-0.51	1.07	-0.48	0.63	Individual Wealth	586.08	671.04	450	504
educ6	0.48	0.99	0.49	0.63	Individual Wealth	586.08	671.04	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	-15.24	851.48	-0.02	0.99	Individual Wealth	586.08	671.04	450	504
empl3	1.35	1.42	0.95	0.34	Individual Wealth	586.08	671.04	450	504
empl4	0.65	1.61	0.41	0.69	Individual Wealth	586.08	671.04	450	504
empl5	2.61	1.53	1.71	0.09	Individual Wealth	586.08	671.04	450	504
empl6	-15.21	1162.09	-0.01	0.99	Individual Wealth	586.08	671.04	450	504
empl7	2.28	1.71	1.34	0.18	Individual Wealth	586.08	671.04	450	504
empl8	2.86	1.78	1.60	0.11	Individual Wealth	586.08	671.04	450	504
empl9	0.64	1.72	0.37	0.71	Individual Wealth	586.08	671.04	450	504
empl10	-1.63	3.31	-0.49	0.62	Individual Wealth	586.08	671.04	450	504
empl11	-19.87	3114.64	-0.01	0.99	Individual Wealth	586.08	671.04	450	504
marr_stat2	-1.44	1.65	-0.87	0.38	Individual Wealth	586.08	671.04	450	504
marr_stat3	0.12	0.62	0.19	0.85	Individual Wealth	586.08	671.04	450	504
marr_stat4	-0.03	0.86	-0.04	0.97	Individual Wealth	586.08	671.04	450	504
marr_stat6	-0.66	0.90	-0.73	0.46	Individual Wealth	586.08	671.04	450	504
average_income	0.00	0.00	2.76	0.01	Individual Wealth	586.08	671.04	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size2	1.36	1.00	1.36	0.17	Individual Wealth	586.08	671.04	450	504
location_size3	1.42	1.03	1.38	0.17	Individual Wealth	586.08	671.04	450	504
location_size4	1.43	1.02	1.40	0.16	Individual Wealth	586.08	671.04	450	504
location_size5	1.67	0.98	1.69	0.09	Individual Wealth	586.08	671.04	450	504
famil_numb	0.28	0.22	1.26	0.21	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:sex2	-1.73	0.64	-2.70	0.01	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:age	0.02	0.03	0.62	0.54	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:educ2	-0.57	1.25	-0.46	0.65	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:educ3	0.82	1.64	0.50	0.62	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:educ4	0.37	1.15	0.32	0.75	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:educ5					Individual Wealth	586.08	671.04	450	504
indivwealth_d1:educ6	-0.15	1.25	-0.12	0.91	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl2	14.54	851.48	0.02	0.99	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl3	-1.19	1.57	-0.76	0.45	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl4	-0.15	1.78	-0.09	0.93	Individual Wealth	586.08	671.04	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:empl5	-2.11	1.68	-1.26	0.21	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl6					Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl7	-2.10	1.85	-1.14	0.26	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl8	-2.25	2.00	-1.13	0.26	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl9	-0.01	1.93	-0.00	1.00	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl10	2.04	3.42	0.60	0.55	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:empl11	19.35	3114.64	0.01	1.00	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:marr_stat2	0.39	1.87	0.21	0.84	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:marr_stat3	-0.27	0.74	-0.37	0.71	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:marr_stat4	-0.47	0.95	-0.50	0.62	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:marr_stat6	-0.13	0.99	-0.13	0.90	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:average_income	-0.00	0.00	-2.54	0.01	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:location_size2	-0.52	1.18	-0.44	0.66	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:location_size3	-0.41	1.21	-0.34	0.74	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:location_size4	-0.13	1.20	-0.11	0.91	Individual Wealth	586.08	671.04	450	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:location_size5	-0.79	1.17	-0.67	0.50	Individual Wealth	586.08	671.04	450	504
indivwealth_d1:famil_numb	-0.26	0.25	-1.02	0.31	Individual Wealth	586.08	671.04	450	504

Table 4: GLM model: UR core vs non-voters

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-6.91	1.30	-5.32	0.00	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1	2.17	2.41	0.90	0.37	Infrastructural development	867.12	1037.60	1258	1316
sex2	0.72	0.23	3.17	0.00	Infrastructural development	867.12	1037.60	1258	1316
age	0.03	0.01	3.31	0.00	Infrastructural development	867.12	1037.60	1258	1316
educ2	0.60	0.68	0.88	0.38	Infrastructural development	867.12	1037.60	1258	1316
educ3	0.24	0.77	0.31	0.76	Infrastructural development	867.12	1037.60	1258	1316
educ4	0.65	0.63	1.03	0.30	Infrastructural development	867.12	1037.60	1258	1316
educ5	-0.12	1.05	-0.11	0.91	Infrastructural development	867.12	1037.60	1258	1316
educ6	0.83	0.66	1.25	0.21	Infrastructural development	867.12	1037.60	1258	1316
empl2	0.31	0.92	0.33	0.74	Infrastructural development	867.12	1037.60	1258	1316
empl3	1.24	0.80	1.55	0.12	Infrastructural development	867.12	1037.60	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl4	1.01	0.81	1.24	0.22	Infrastructural development	867.12	1037.60	1258	1316
empl5	0.86	0.81	1.06	0.29	Infrastructural development	867.12	1037.60	1258	1316
empl6	-14.48	1197.68	-0.01	0.99	Infrastructural development	867.12	1037.60	1258	1316
empl7	1.52	0.82	1.85	0.06	Infrastructural development	867.12	1037.60	1258	1316
empl8	1.68	0.90	1.87	0.06	Infrastructural development	867.12	1037.60	1258	1316
empl9	1.53	0.90	1.70	0.09	Infrastructural development	867.12	1037.60	1258	1316
empl10	0.79	1.03	0.77	0.44	Infrastructural development	867.12	1037.60	1258	1316
empl11	-0.25	1.88	-0.13	0.89	Infrastructural development	867.12	1037.60	1258	1316
marr_stat2	-0.99	0.77	-1.29	0.20	Infrastructural development	867.12	1037.60	1258	1316
marr_stat3	-0.50	0.31	-1.60	0.11	Infrastructural development	867.12	1037.60	1258	1316
marr_stat4	-0.76	0.34	-2.20	0.03	Infrastructural development	867.12	1037.60	1258	1316
marr_stat5	-17.23	2527.01	-0.01	0.99	Infrastructural development	867.12	1037.60	1258	1316
marr_stat6	-0.29	0.35	-0.82	0.41	Infrastructural development	867.12	1037.60	1258	1316
average_income	0.00	0.00	2.27	0.02	Infrastructural development	867.12	1037.60	1258	1316
location_size2	1.55	0.42	3.66	0.00	Infrastructural development	867.12	1037.60	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size3	1.23	0.44	2.76	0.01	Infrastructural development	867.12	1037.60	1258	1316
location_size4	1.00	0.45	2.24	0.03	Infrastructural development	867.12	1037.60	1258	1316
location_size5	1.40	0.44	3.19	0.00	Infrastructural development	867.12	1037.60	1258	1316
famil_numb	-0.03	0.09	-0.33	0.74	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:sex2	0.62	0.50	1.25	0.21	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:age	-0.03	0.02	-1.11	0.27	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:educ2	-0.57	1.23	-0.46	0.64	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:educ3	-17.57	1594.98	-0.01	0.99	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:educ4	-1.22	1.17	-1.04	0.30	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:educ5	-16.35	1835.03	-0.01	0.99	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:educ6	-1.35	1.26	-1.08	0.28	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl2	-19.15	1538.49	-0.01	0.99	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl3	-2.47	1.16	-2.13	0.03	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl4	-2.38	1.25	-1.91	0.06	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl5	-1.47	1.17	-1.25	0.21	Infrastructural development	867.12	1037.60	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:empl6	-3.25	2114.80	-0.00	1.00	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl7	-2.33	1.25	-1.86	0.06	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl8	0.01	1.42	0.01	0.99	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl9	-2.31	1.45	-1.59	0.11	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl10	-17.38	1665.80	-0.01	0.99	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:empl11	-16.50	3311.72	-0.00	1.00	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:marr_stat2	-0.77	1.44	-0.53	0.59	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:marr_stat3	0.28	0.73	0.38	0.70	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:marr_stat4	0.03	0.74	0.04	0.97	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:marr_stat5	-1.93	3846.27	-0.00	1.00	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:marr_stat6	-1.17	0.90	-1.30	0.19	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:average_income	0.00	0.00	2.71	0.01	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:location_size2	-0.61	0.98	-0.63	0.53	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:location_size3	-0.01	1.00	-0.01	1.00	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:location_size4	0.50	0.94	0.53	0.59	Infrastructural development	867.12	1037.60	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:location_size5	0.11	0.96	0.12	0.91	Infrastructural development	867.12	1037.60	1258	1316
infrastr_d1:famil_numb	0.28	0.22	1.27	0.20	Infrastructural development	867.12	1037.60	1258	1316
(Intercept)	-3.78	0.90	-4.21	0.00	Social Support	903.44	1056.19	1258	1316
socialsup_d1	-17.68	1539.06	-0.01	0.99	Social Support	903.44	1056.19	1258	1316
sex2	0.64	0.19	3.31	0.00	Social Support	903.44	1056.19	1258	1316
age	0.02	0.01	2.50	0.01	Social Support	903.44	1056.19	1258	1316
educ2	0.30	0.51	0.58	0.56	Social Support	903.44	1056.19	1258	1316
educ3	0.13	0.59	0.22	0.82	Social Support	903.44	1056.19	1258	1316
educ4	-0.15	0.46	-0.33	0.74	Social Support	903.44	1056.19	1258	1316
educ5	-0.74	0.87	-0.84	0.40	Social Support	903.44	1056.19	1258	1316
educ6	0.46	0.48	0.96	0.34	Social Support	903.44	1056.19	1258	1316
empl2	-0.64	0.58	-1.09	0.28	Social Support	903.44	1056.19	1258	1316
empl3	-0.51	0.41	-1.25	0.21	Social Support	903.44	1056.19	1258	1316
empl4	-0.65	0.46	-1.41	0.16	Social Support	903.44	1056.19	1258	1316
empl5	-0.52	0.40	-1.31	0.19	Social Support	903.44	1056.19	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl6	-16.80	906.54	-0.02	0.99	Social Support	903.44	1056.19	1258	1316
empl7	-0.14	0.46	-0.31	0.76	Social Support	903.44	1056.19	1258	1316
empl8	1.31	0.55	2.38	0.02	Social Support	903.44	1056.19	1258	1316
empl9	-1.11	0.65	-1.70	0.09	Social Support	903.44	1056.19	1258	1316
empl10	-0.90	0.56	-1.61	0.11	Social Support	903.44	1056.19	1258	1316
empl11	-1.92	1.22	-1.57	0.12	Social Support	903.44	1056.19	1258	1316
marr_stat2	-1.20	0.65	-1.84	0.07	Social Support	903.44	1056.19	1258	1316
marr_stat3	-0.61	0.39	-1.58	0.11	Social Support	903.44	1056.19	1258	1316
marr_stat4	-0.24	0.28	-0.86	0.39	Social Support	903.44	1056.19	1258	1316
marr_stat5	-18.01	2401.44	-0.01	0.99	Social Support	903.44	1056.19	1258	1316
marr_stat6	-0.54	0.30	-1.78	0.07	Social Support	903.44	1056.19	1258	1316
average_income	0.00	0.00	1.23	0.22	Social Support	903.44	1056.19	1258	1316
location_size2	0.52	0.38	1.36	0.17	Social Support	903.44	1056.19	1258	1316
location_size3	1.29	0.37	3.47	0.00	Social Support	903.44	1056.19	1258	1316
location_size4	0.97	0.38	2.53	0.01	Social Support	903.44	1056.19	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	1.20	0.38	3.18	0.00	Social Support	903.44	1056.19	1258	1316
famil_numb	0.06	0.08	0.75	0.45	Social Support	903.44	1056.19	1258	1316
socialsup_d1:sex2	0.73	0.63	1.15	0.25	Social Support	903.44	1056.19	1258	1316
socialsup_d1:age	0.01	0.03	0.50	0.62	Social Support	903.44	1056.19	1258	1316
socialsup_d1:educ2	-0.52	1.40	-0.37	0.71	Social Support	903.44	1056.19	1258	1316
socialsup_d1:educ3	-0.62	1.73	-0.36	0.72	Social Support	903.44	1056.19	1258	1316
socialsup_d1:educ4	-0.99	1.16	-0.85	0.39	Social Support	903.44	1056.19	1258	1316
socialsup_d1:educ5	-15.50	2072.87	-0.01	0.99	Social Support	903.44	1056.19	1258	1316
socialsup_d1:educ6	-0.62	1.20	-0.51	0.61	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl2	-0.46	2235.85	-0.00	1.00	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl3	16.98	1539.06	0.01	0.99	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl4	16.48	1539.06	0.01	0.99	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl5	16.39	1539.06	0.01	0.99	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl6	18.73	2367.37	0.01	0.99	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl7	16.24	1539.06	0.01	0.99	Social Support	903.44	1056.19	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:empl8	-1.50	2567.19	-0.00	1.00	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl9	17.14	1539.06	0.01	0.99	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl10	16.64	1539.06	0.01	0.99	Social Support	903.44	1056.19	1258	1316
socialsup_d1:empl11	1.30	2512.67	0.00	1.00	Social Support	903.44	1056.19	1258	1316
socialsup_d1:marr_stat2	-14.77	1701.16	-0.01	0.99	Social Support	903.44	1056.19	1258	1316
socialsup_d1:marr_stat3	0.26	0.92	0.29	0.78	Social Support	903.44	1056.19	1258	1316
socialsup_d1:marr_stat4	-0.02	0.80	-0.03	0.98	Social Support	903.44	1056.19	1258	1316
socialsup_d1:marr_stat5	1.28	6647.13	0.00	1.00	Social Support	903.44	1056.19	1258	1316
socialsup_d1:marr_stat6	-0.98	1.22	-0.80	0.42	Social Support	903.44	1056.19	1258	1316
socialsup_d1:average_income	0.00	0.00	0.86	0.39	Social Support	903.44	1056.19	1258	1316
socialsup_d1:location_size2	0.34	0.96	0.36	0.72	Social Support	903.44	1056.19	1258	1316
socialsup_d1:location_size3	-1.05	1.05	-0.99	0.32	Social Support	903.44	1056.19	1258	1316
socialsup_d1:location_size4	-0.09	1.04	-0.08	0.93	Social Support	903.44	1056.19	1258	1316
socialsup_d1:location_size5	0.05	1.01	0.05	0.96	Social Support	903.44	1056.19	1258	1316
socialsup_d1:famil_numb	0.11	0.17	0.64	0.52	Social Support	903.44	1056.19	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-6.06	0.99	-6.09	0.00	Economic Development	957.04	1117.05	1258	1316
econdev_d1	3.45	2.47	1.40	0.16	Economic Development	957.04	1117.05	1258	1316
sex2	0.48	0.20	2.35	0.02	Economic Development	957.04	1117.05	1258	1316
age	0.05	0.01	5.08	0.00	Economic Development	957.04	1117.05	1258	1316
educ2	0.50	0.49	1.02	0.31	Economic Development	957.04	1117.05	1258	1316
educ3	0.11	0.65	0.18	0.86	Economic Development	957.04	1117.05	1258	1316
educ4	-0.06	0.45	-0.14	0.89	Economic Development	957.04	1117.05	1258	1316
educ5	1.82	0.93	1.95	0.05	Economic Development	957.04	1117.05	1258	1316
educ6	0.44	0.49	0.90	0.37	Economic Development	957.04	1117.05	1258	1316
empl2	-0.92	0.89	-1.03	0.30	Economic Development	957.04	1117.05	1258	1316
empl3	0.28	0.51	0.55	0.58	Economic Development	957.04	1117.05	1258	1316
empl4	0.17	0.53	0.32	0.75	Economic Development	957.04	1117.05	1258	1316
empl5	0.23	0.49	0.47	0.64	Economic Development	957.04	1117.05	1258	1316
empl6	-14.52	645.21	-0.02	0.98	Economic Development	957.04	1117.05	1258	1316
empl7	0.56	0.53	1.06	0.29	Economic Development	957.04	1117.05	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl8	-0.25	0.72	-0.36	0.72	Economic Development	957.04	1117.05	1258	1316
empl9	-0.07	0.70	-0.10	0.92	Economic Development	957.04	1117.05	1258	1316
empl10	-0.28	0.77	-0.37	0.71	Economic Development	957.04	1117.05	1258	1316
empl11	-0.25	0.68	-0.36	0.72	Economic Development	957.04	1117.05	1258	1316
marr_stat2	-0.85	0.60	-1.41	0.16	Economic Development	957.04	1117.05	1258	1316
marr_stat3	-0.64	0.31	-2.07	0.04	Economic Development	957.04	1117.05	1258	1316
marr_stat4	0.05	0.29	0.19	0.85	Economic Development	957.04	1117.05	1258	1316
marr_stat5	-16.57	1303.63	-0.01	0.99	Economic Development	957.04	1117.05	1258	1316
marr_stat6	-0.60	0.32	-1.91	0.06	Economic Development	957.04	1117.05	1258	1316
average_income	0.00	0.00	2.68	0.01	Economic Development	957.04	1117.05	1258	1316
location_size2	0.78	0.40	1.93	0.05	Economic Development	957.04	1117.05	1258	1316
location_size3	0.47	0.40	1.18	0.24	Economic Development	957.04	1117.05	1258	1316
location_size4	0.96	0.41	2.35	0.02	Economic Development	957.04	1117.05	1258	1316
location_size5	0.77	0.42	1.84	0.07	Economic Development	957.04	1117.05	1258	1316
famil numb	0.22	0.07	3.18	0.00	Economic Development	957.04	1117.05	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:sex2	0.20	0.57	0.35	0.73	Economic Development	957.04	1117.05	1258	1316
econdev_d1:age	-0.02	0.02	-0.78	0.44	Economic Development	957.04	1117.05	1258	1316
econdev_d1:educ2	-1.75	1.15	-1.53	0.13	Economic Development	957.04	1117.05	1258	1316
econdev_d1:educ3	-2.45	1.58	-1.55	0.12	Economic Development	957.04	1117.05	1258	1316
econdev_d1:educ4	-0.84	1.05	-0.80	0.42	Economic Development	957.04	1117.05	1258	1316
econdev_d1:educ5	-17.77	1650.36	-0.01	0.99	Economic Development	957.04	1117.05	1258	1316
econdev_d1:educ6	-2.25	1.21	-1.86	0.06	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl2	1.15	1.78	0.65	0.52	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl3	-0.01	1.32	-0.01	0.99	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl4	-1.61	1.63	-0.99	0.32	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl5	-1.07	1.35	-0.80	0.43	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl6	0.11	1467.00	0.00	1.00	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl7	-0.90	1.40	-0.64	0.52	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl8	0.26	1.65	0.15	0.88	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl9	-0.33	1.73	-0.19	0.85	Economic Development	957.04	1117.05	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:empl10	0.79	1.59	0.50	0.62	Economic Development	957.04	1117.05	1258	1316
econdev_d1:empl11	-15.48	1093.05	-0.01	0.99	Economic Development	957.04	1117.05	1258	1316
econdev_d1:marr_stat2	-14.28	946.54	-0.02	0.99	Economic Development	957.04	1117.05	1258	1316
econdev_d1:marr_stat3	1.61	0.71	2.28	0.02	Economic Development	957.04	1117.05	1258	1316
econdev_d1:marr_stat4	-0.35	0.69	-0.51	0.61	Economic Development	957.04	1117.05	1258	1316
econdev_d1:marr_stat5	1.81	2884.34	0.00	1.00	Economic Development	957.04	1117.05	1258	1316
econdev_d1:marr_stat6	0.04	0.90	0.05	0.96	Economic Development	957.04	1117.05	1258	1316
econdev_d1:average_income	-0.00	0.00	-0.19	0.85	Economic Development	957.04	1117.05	1258	1316
econdev_d1:location_size2	-0.99	1.05	-0.94	0.35	Economic Development	957.04	1117.05	1258	1316
econdev_d1:location_size3	-0.27	1.02	-0.27	0.79	Economic Development	957.04	1117.05	1258	1316
econdev_d1:location_size4	-0.98	1.01	-0.97	0.33	Economic Development	957.04	1117.05	1258	1316
econdev_d1:location_size5	-0.11	1.00	-0.11	0.91	Economic Development	957.04	1117.05	1258	1316
econdev_d1:famil_numb	-0.19	0.22	-0.86	0.39	Economic Development	957.04	1117.05	1258	1316
(Intercept)	-30.26	11667.30	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1	24.75	11667.31	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
sex2	3.42	19.90	0.17	0.86	Personal Connections	943.80	1107.96	1259	1316
age	0.06	0.78	0.08	0.94	Personal Connections	943.80	1107.96	1259	1316
educ2	-18.15	9872.45	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
educ3	-4.38	32.80	-0.13	0.89	Personal Connections	943.80	1107.96	1259	1316
educ4	-3.81	29.13	-0.13	0.90	Personal Connections	943.80	1107.96	1259	1316
educ5	-22.90	30858.68	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
educ6	-3.09	28.17	-0.11	0.91	Personal Connections	943.80	1107.96	1259	1316
empl2	-22.01	15503.96	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
empl3	1.22	29.79	0.04	0.97	Personal Connections	943.80	1107.96	1259	1316
empl4	3.69	43.59	0.08	0.93	Personal Connections	943.80	1107.96	1259	1316
empl5	1.34	32.65	0.04	0.97	Personal Connections	943.80	1107.96	1259	1316
empl6	3.28	19043.87	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
empl7	-0.99	34.64	-0.03	0.98	Personal Connections	943.80	1107.96	1259	1316
empl8	-13.53	18119.11	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
empl9	4.12	35.02	0.12	0.91	Personal Connections	943.80	1107.96	1259	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl10	2.07	39.59	0.05	0.96	Personal Connections	943.80	1107.96	1259	1316
empl11	-12.95	19007.42	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
marr_stat2	-19.63	16698.78	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
marr_stat3	0.85	19.82	0.04	0.97	Personal Connections	943.80	1107.96	1259	1316
marr_stat4	-0.80	22.02	-0.04	0.97	Personal Connections	943.80	1107.96	1259	1316
marr_stat5	-17.44	17876.86	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
marr_stat6	-19.64	8785.67	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
average_income	0.00	0.00	0.26	0.80	Personal Connections	943.80	1107.96	1259	1316
location_size2	22.01	11667.04	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
location_size3	20.85	11667.07	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
location_size4	21.07	11667.03	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
location_size5	17.05	11667.00	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
famil_numb	0.04	7.66	0.01	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:sex2	-2.72	19.97	-0.14	0.89	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:age	-0.03	0.78	-0.04	0.97	Personal Connections	943.80	1107.96	1259	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:educ2	18.37	9872.45	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:educ3	4.35	33.26	0.13	0.90	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:educ4	3.85	29.42	0.13	0.90	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:educ5	23.22	30858.68	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:educ6	3.32	28.50	0.12	0.91	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl2	21.86	15503.96	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl3	-0.77	30.10	-0.03	0.98	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl4	-3.50	43.84	-0.08	0.94	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl5	-1.07	32.94	-0.03	0.97	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl6	-19.00	20666.60	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl7	1.66	34.94	0.05	0.96	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl8	14.64	18119.11	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl9	-3.76	35.46	-0.11	0.92	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl10	-1.92	39.97	-0.05	0.96	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:empl11	11.95	19007.43	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:marr_stat2	18.68	16698.78	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:marr_stat3	-1.14	19.97	-0.06	0.95	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:marr_stat4	0.59	22.15	0.03	0.98	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:marr_stat5					Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:marr_stat6	19.33	8785.67	0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:average_income	-0.00	0.00	-0.24	0.81	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:location_size2	-21.23	11667.04	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:location_size3	-19.89	11667.07	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:location_size4	-19.86	11667.03	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:location_size5	-15.84	11667.00	-0.00	1.00	Personal Connections	943.80	1107.96	1259	1316
personconnect_d1:famil_numb	0.11	7.68	0.01	0.99	Personal Connections	943.80	1107.96	1259	1316
(Intercept)	-5.55	2.00	-2.78	0.01	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1	-0.06	2.29	-0.03	0.98	Individual Wealth	920.87	1090.93	1258	1316
sex2	1.87	0.46	4.11	0.00	Individual Wealth	920.87	1090.93	1258	1316
age	0.05	0.02	2.54	0.01	Individual Wealth	920.87	1090.93	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ2	-1.39	0.78	-1.79	0.07	Individual Wealth	920.87	1090.93	1258	1316
educ3	-1.42	1.08	-1.32	0.19	Individual Wealth	920.87	1090.93	1258	1316
educ4	-2.08	0.77	-2.69	0.01	Individual Wealth	920.87	1090.93	1258	1316
educ5	-16.22	1100.96	-0.01	0.99	Individual Wealth	920.87	1090.93	1258	1316
educ6	-1.99	0.86	-2.30	0.02	Individual Wealth	920.87	1090.93	1258	1316
empl2	-15.18	878.03	-0.02	0.99	Individual Wealth	920.87	1090.93	1258	1316
empl3	1.19	1.11	1.07	0.29	Individual Wealth	920.87	1090.93	1258	1316
empl4	0.49	1.25	0.39	0.69	Individual Wealth	920.87	1090.93	1258	1316
empl5	0.71	1.13	0.63	0.53	Individual Wealth	920.87	1090.93	1258	1316
empl6	-13.77	934.67	-0.01	0.99	Individual Wealth	920.87	1090.93	1258	1316
empl7	0.26	1.13	0.23	0.82	Individual Wealth	920.87	1090.93	1258	1316
empl8	2.46	1.30	1.89	0.06	Individual Wealth	920.87	1090.93	1258	1316
empl9	1.08	1.44	0.75	0.45	Individual Wealth	920.87	1090.93	1258	1316
empl10	-2.19	2.95	-0.74	0.46	Individual Wealth	920.87	1090.93	1258	1316
empl11	-14.37	1250.13	-0.01	0.99	Individual Wealth	920.87	1090.93	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-1.52	1.44	-1.05	0.29	Individual Wealth	920.87	1090.93	1258	1316
marr_stat3	0.14	0.56	0.24	0.81	Individual Wealth	920.87	1090.93	1258	1316
marr_stat4	-0.81	0.59	-1.38	0.17	Individual Wealth	920.87	1090.93	1258	1316
marr_stat5	-15.50	2239.60	-0.01	0.99	Individual Wealth	920.87	1090.93	1258	1316
marr_stat6	-0.51	0.72	-0.70	0.48	Individual Wealth	920.87	1090.93	1258	1316
average_income	0.00	0.00	2.40	0.02	Individual Wealth	920.87	1090.93	1258	1316
location_size2	-0.00	0.81	-0.00	1.00	Individual Wealth	920.87	1090.93	1258	1316
location_size3	0.44	0.81	0.54	0.59	Individual Wealth	920.87	1090.93	1258	1316
location_size4	-0.42	0.82	-0.52	0.61	Individual Wealth	920.87	1090.93	1258	1316
location_size5	0.78	0.78	0.99	0.32	Individual Wealth	920.87	1090.93	1258	1316
famil_numb	0.17	0.14	1.25	0.21	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:sex2	-1.44	0.50	-2.86	0.00	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:age	-0.02	0.02	-0.99	0.32	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:educ2	1.80	0.98	1.84	0.07	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:educ3	2.13	1.28	1.66	0.10	Individual Wealth	920.87	1090.93	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:educ4	2.50	0.94	2.65	0.01	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:educ5	16.70	1100.96	0.02	0.99	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:educ6	2.68	1.03	2.60	0.01	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl2	15.54	878.03	0.02	0.99	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl3	-0.61	1.23	-0.49	0.62	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl4	0.03	1.38	0.02	0.98	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl5	-0.33	1.26	-0.26	0.79	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl6	-0.44	1114.62	-0.00	1.00	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl7	0.51	1.27	0.40	0.69	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl8	-1.33	1.48	-0.90	0.37	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl9	-0.33	1.59	-0.21	0.83	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl10	2.89	3.03	0.95	0.34	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:empl11	13.79	1250.13	0.01	0.99	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:marr_stat2	0.47	1.63	0.29	0.78	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:marr_stat3	-0.39	0.64	-0.60	0.55	Individual Wealth	920.87	1090.93	1258	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:marr_stat4	0.82	0.67	1.22	0.22	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:marr_stat5	-1.16	2814.08	-0.00	1.00	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:marr_stat6	-0.02	0.80	-0.03	0.98	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:average_income	-0.00	0.00	-1.11	0.27	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:location_size2	1.06	0.96	1.10	0.27	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:location_size3	0.59	0.96	0.62	0.54	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:location_size4	1.87	0.97	1.93	0.05	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:location_size5	0.39	0.94	0.41	0.68	Individual Wealth	920.87	1090.93	1258	1316
indivwealth_d1:famil_numb	-0.12	0.16	-0.70	0.49	Individual Wealth	920.87	1090.93	1258	1316

Table 5: GLM model: UR swing vs other/non-voters

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-2.78	0.84	-3.30	0.00	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1	0.94	1.57	0.60	0.55	Infrastructural development	1379.84	1507.64	1364	1422
sex2	0.50	0.19	2.64	0.01	Infrastructural development	1379.84	1507.64	1364	1422
age	0.03	0.01	3.58	0.00	Infrastructural development	1379.84	1507.64	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ2	-0.91	0.48	-1.88	0.06	Infrastructural development	1379.84	1507.64	1364	1422
educ3	-1.78	0.70	-2.53	0.01	Infrastructural development	1379.84	1507.64	1364	1422
educ4	-0.33	0.43	-0.77	0.44	Infrastructural development	1379.84	1507.64	1364	1422
educ5	-1.78	0.84	-2.13	0.03	Infrastructural development	1379.84	1507.64	1364	1422
educ6	-0.54	0.46	-1.17	0.24	Infrastructural development	1379.84	1507.64	1364	1422
empl2	-0.45	0.50	-0.90	0.37	Infrastructural development	1379.84	1507.64	1364	1422
empl3	-0.28	0.40	-0.71	0.48	Infrastructural development	1379.84	1507.64	1364	1422
empl4	-1.16	0.44	-2.63	0.01	Infrastructural development	1379.84	1507.64	1364	1422
empl5	-0.62	0.40	-1.55	0.12	Infrastructural development	1379.84	1507.64	1364	1422
empl6	-0.75	0.84	-0.89	0.37	Infrastructural development	1379.84	1507.64	1364	1422
empl7	-0.32	0.44	-0.72	0.47	Infrastructural development	1379.84	1507.64	1364	1422
empl8	-0.25	0.55	-0.46	0.65	Infrastructural development	1379.84	1507.64	1364	1422
empl9	0.35	0.51	0.68	0.50	Infrastructural development	1379.84	1507.64	1364	1422
empl10	0.01	0.52	0.01	0.99	Infrastructural development	1379.84	1507.64	1364	1422
empl11	-0.85	1.05	-0.81	0.42	Infrastructural development	1379.84	1507.64	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	0.33	0.43	0.77	0.44	Infrastructural development	1379.84	1507.64	1364	1422
marr_stat3	-0.34	0.31	-1.08	0.28	Infrastructural development	1379.84	1507.64	1364	1422
marr_stat4	0.15	0.27	0.56	0.58	Infrastructural development	1379.84	1507.64	1364	1422
marr_stat5	-15.37	920.97	-0.02	0.99	Infrastructural development	1379.84	1507.64	1364	1422
marr_stat6	0.06	0.28	0.21	0.83	Infrastructural development	1379.84	1507.64	1364	1422
average_income	0.00	0.00	0.11	0.91	Infrastructural development	1379.84	1507.64	1364	1422
location_size2	0.31	0.31	0.99	0.32	Infrastructural development	1379.84	1507.64	1364	1422
location_size3	0.24	0.33	0.74	0.46	Infrastructural development	1379.84	1507.64	1364	1422
location_size4	0.25	0.32	0.80	0.42	Infrastructural development	1379.84	1507.64	1364	1422
location_size5	0.26	0.33	0.79	0.43	Infrastructural development	1379.84	1507.64	1364	1422
famil_numb	0.13	0.08	1.59	0.11	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:sex2	0.09	0.34	0.27	0.79	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:age	-0.01	0.02	-0.46	0.64	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:educ2	-0.04	0.91	-0.05	0.96	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:educ3	1.06	1.12	0.94	0.35	Infrastructural development	1379.84	1507.64	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:educ4	-0.69	0.82	-0.83	0.40	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:educ5	-14.38	764.43	-0.02	0.98	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:educ6	-0.82	0.89	-0.93	0.35	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl2	1.37	0.91	1.50	0.13	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl3	0.13	0.78	0.17	0.86	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl4	0.93	0.83	1.12	0.26	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl5	-0.05	0.80	-0.06	0.95	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl6	-14.31	779.29	-0.02	0.99	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl7	0.17	0.84	0.20	0.84	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl8	0.67	1.06	0.64	0.52	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl9	-0.15	1.04	-0.15	0.88	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl10	-0.12	1.02	-0.12	0.91	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:empl11	0.68	1.71	0.40	0.69	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:marr_stat2	-0.52	0.79	-0.66	0.51	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:marr_stat3	-0.19	0.54	-0.35	0.72	Infrastructural development	1379.84	1507.64	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:marr_stat4	-0.78	0.53	-1.46	0.14	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:marr_stat5	-0.13	1647.74	-0.00	1.00	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:marr_stat6	-0.15	0.51	-0.29	0.77	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:average_income	0.00	0.00	1.22	0.22	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:location_size2	0.04	0.54	0.08	0.94	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:location_size3	-0.38	0.60	-0.63	0.53	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:location_size4	-0.15	0.56	-0.27	0.79	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:location_size5	0.00	0.56	0.01	0.99	Infrastructural development	1379.84	1507.64	1364	1422
infrastr_d1:famil numb	-0.04	0.14	-0.28	0.78	Infrastructural development	1379.84	1507.64	1364	1422
(Intercept)	-2.05	0.75	-2.74	0.01	Social Support	1351.55	1493.73	1364	1422
socialsup_d1	-2.16	1.92	-1.12	0.26	Social Support	1351.55	1493.73	1364	1422
sex2	0.42	0.17	2.53	0.01	Social Support	1351.55	1493.73	1364	1422
age	0.02	0.01	2.64	0.01	Social Support	1351.55	1493.73	1364	1422
educ2	-0.75	0.43	-1.74	0.08	Social Support	1351.55	1493.73	1364	1422
educ3	-0.78	0.57	-1.36	0.17	Social Support	1351.55	1493.73	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ4	-0.25	0.37	-0.67	0.50	Social Support	1351.55	1493.73	1364	1422
educ5	-2.22	0.83	-2.67	0.01	Social Support	1351.55	1493.73	1364	1422
educ6	-0.48	0.40	-1.19	0.24	Social Support	1351.55	1493.73	1364	1422
empl2	0.78	0.44	1.78	0.08	Social Support	1351.55	1493.73	1364	1422
empl3	-0.46	0.37	-1.25	0.21	Social Support	1351.55	1493.73	1364	1422
empl4	-0.65	0.41	-1.59	0.11	Social Support	1351.55	1493.73	1364	1422
empl5	-0.83	0.37	-2.28	0.02	Social Support	1351.55	1493.73	1364	1422
empl6	-0.32	0.50	-0.64	0.52	Social Support	1351.55	1493.73	1364	1422
empl7	-0.29	0.42	-0.69	0.49	Social Support	1351.55	1493.73	1364	1422
empl8	0.11	0.60	0.18	0.86	Social Support	1351.55	1493.73	1364	1422
empl9	-0.14	0.51	-0.28	0.78	Social Support	1351.55	1493.73	1364	1422
empl10	-0.04	0.44	-0.09	0.93	Social Support	1351.55	1493.73	1364	1422
empl11	1.27	0.49	2.61	0.01	Social Support	1351.55	1493.73	1364	1422
marr_stat2	-0.32	0.48	-0.68	0.50	Social Support	1351.55	1493.73	1364	1422
marr_stat3	0.05	0.33	0.16	0.87	Social Support	1351.55	1493.73	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat4	0.25	0.24	1.04	0.30	Social Support	1351.55	1493.73	1364	1422
marr_stat5	-15.47	947.80	-0.02	0.99	Social Support	1351.55	1493.73	1364	1422
marr_stat6	0.46	0.23	1.97	0.05	Social Support	1351.55	1493.73	1364	1422
average_income	-0.00	0.00	-0.50	0.62	Social Support	1351.55	1493.73	1364	1422
location_size2	-0.25	0.28	-0.88	0.38	Social Support	1351.55	1493.73	1364	1422
location_size3	-0.50	0.31	-1.62	0.11	Social Support	1351.55	1493.73	1364	1422
location_size4	-0.13	0.29	-0.45	0.65	Social Support	1351.55	1493.73	1364	1422
location_size5	0.11	0.29	0.38	0.70	Social Support	1351.55	1493.73	1364	1422
famil_numb	0.17	0.07	2.42	0.02	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:sex2	0.66	0.43	1.53	0.13	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:age	0.01	0.02	0.43	0.67	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:educ2	1.31	1.20	1.10	0.27	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:educ3	-0.01	1.44	-0.01	0.99	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:educ4	0.40	1.09	0.36	0.72	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:educ5	-12.87	791.40	-0.02	0.99	Social Support	1351.55	1493.73	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:educ6	0.50	1.11	0.45	0.65	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl2	-1.32	1.05	-1.26	0.21	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl3	-0.10	0.83	-0.12	0.90	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl4	-0.29	0.92	-0.31	0.75	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl5	-0.03	0.80	-0.03	0.97	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl6	-15.10	619.06	-0.02	0.98	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl7	-0.32	0.93	-0.35	0.73	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl8	-1.11	1.45	-0.76	0.45	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl9	0.87	1.12	0.77	0.44	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl10	-0.43	1.02	-0.42	0.67	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:empl11	-3.05	1.39	-2.19	0.03	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:marr_stat2	0.68	0.93	0.73	0.46	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:marr_stat3	-0.39	0.88	-0.44	0.66	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:marr_stat4	-0.61	0.61	-0.99	0.32	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:marr_stat5	0.66	2607.38	0.00	1.00	Social Support	1351.55	1493.73	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:marr_stat6	-0.63	0.58	-1.09	0.27	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:average_income	0.00	0.00	1.96	0.05	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:location_size2	0.40	0.67	0.59	0.55	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:location_size3	0.08	0.77	0.11	0.91	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:location_size4	0.65	0.71	0.90	0.37	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:location_size5	0.26	0.70	0.37	0.71	Social Support	1351.55	1493.73	1364	1422
socialsup_d1:famil_numb	0.14	0.14	0.99	0.32	Social Support	1351.55	1493.73	1364	1422
(Intercept)	-2.60	0.84	-3.10	0.00	Economic Development	1333.59	1450.03	1364	1422
econdev_d1	-0.33	2.04	-0.16	0.87	Economic Development	1333.59	1450.03	1364	1422
sex2	0.61	0.18	3.29	0.00	Economic Development	1333.59	1450.03	1364	1422
age	0.01	0.01	1.38	0.17	Economic Development	1333.59	1450.03	1364	1422
educ2	0.10	0.43	0.24	0.81	Economic Development	1333.59	1450.03	1364	1422
educ3	0.11	0.53	0.21	0.83	Economic Development	1333.59	1450.03	1364	1422
educ4	-0.03	0.40	-0.09	0.93	Economic Development	1333.59	1450.03	1364	1422
educ5	0.49	0.89	0.56	0.58	Economic Development	1333.59	1450.03	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	-0.68	0.45	-1.51	0.13	Economic Development	1333.59	1450.03	1364	1422
empl2	1.46	0.57	2.55	0.01	Economic Development	1333.59	1450.03	1364	1422
empl3	0.47	0.50	0.94	0.35	Economic Development	1333.59	1450.03	1364	1422
empl4	-0.03	0.53	-0.05	0.96	Economic Development	1333.59	1450.03	1364	1422
empl5	0.20	0.48	0.41	0.68	Economic Development	1333.59	1450.03	1364	1422
empl6	-0.70	0.75	-0.93	0.35	Economic Development	1333.59	1450.03	1364	1422
empl7	1.09	0.52	2.09	0.04	Economic Development	1333.59	1450.03	1364	1422
empl8	0.83	0.63	1.31	0.19	Economic Development	1333.59	1450.03	1364	1422
empl9	0.85	0.58	1.45	0.15	Economic Development	1333.59	1450.03	1364	1422
empl10	0.71	0.57	1.25	0.21	Economic Development	1333.59	1450.03	1364	1422
empl11	-0.06	0.69	-0.08	0.93	Economic Development	1333.59	1450.03	1364	1422
marr_stat2	0.09	0.40	0.24	0.81	Economic Development	1333.59	1450.03	1364	1422
marr_stat3	-0.33	0.28	-1.18	0.24	Economic Development	1333.59	1450.03	1364	1422
marr_stat4	0.29	0.27	1.10	0.27	Economic Development	1333.59	1450.03	1364	1422
marr_stat5	-14.58	521.66	-0.03	0.98	Economic Development	1333.59	1450.03	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat6	0.53	0.23	2.29	0.02	Economic Development	1333.59	1450.03	1364	1422
average_income	0.00	0.00	0.15	0.88	Economic Development	1333.59	1450.03	1364	1422
location_size2	-0.52	0.30	-1.71	0.09	Economic Development	1333.59	1450.03	1364	1422
location_size3	-0.75	0.30	-2.48	0.01	Economic Development	1333.59	1450.03	1364	1422
location_size4	-0.35	0.30	-1.17	0.24	Economic Development	1333.59	1450.03	1364	1422
location_size5	-0.50	0.31	-1.61	0.11	Economic Development	1333.59	1450.03	1364	1422
famil_numb	0.13	0.06	1.98	0.05	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:sex2	-0.40	0.43	-0.93	0.35	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:age	0.03	0.02	1.41	0.16	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:educ2	-1.26	0.92	-1.37	0.17	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:educ3	-1.89	1.23	-1.53	0.13	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:educ4	-0.80	0.84	-0.95	0.34	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:educ5	-15.20	709.82	-0.02	0.98	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:educ6	-0.58	0.94	-0.61	0.54	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl2	-0.97	1.37	-0.71	0.48	Economic Development	1333.59	1450.03	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:empl3	0.46	1.11	0.41	0.68	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl4	0.01	1.16	0.01	0.99	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl5	-0.98	1.11	-0.88	0.38	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl6	0.67	1.69	0.39	0.69	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl7	-1.05	1.19	-0.88	0.38	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl8	-1.09	1.49	-0.73	0.46	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl9	0.29	1.30	0.22	0.83	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl10	-0.70	1.33	-0.53	0.60	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:empl11	-0.96	1.61	-0.60	0.55	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:marr_stat2	0.29	0.88	0.32	0.75	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:marr_stat3	0.49	0.68	0.72	0.47	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:marr_stat4	-0.69	0.69	-1.00	0.32	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:marr_stat5	1.91	1166.83	0.00	1.00	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:marr_stat6	-0.07	0.59	-0.11	0.91	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:average_income	-0.00	0.00	-0.13	0.90	Economic Development	1333.59	1450.03	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:location_size2	0.50	0.75	0.67	0.50	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:location_size3	0.72	0.77	0.94	0.35	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:location_size4	0.47	0.73	0.65	0.52	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:location_size5	1.03	0.75	1.37	0.17	Economic Development	1333.59	1450.03	1364	1422
econdev_d1:famil_numb	0.01	0.17	0.07	0.95	Economic Development	1333.59	1450.03	1364	1422
(Intercept)	-8.67	4.24	-2.04	0.04	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1	6.25	4.32	1.45	0.15	Personal Connections	1358.46	1488.62	1365	1422
sex2	-0.14	0.58	-0.24	0.81	Personal Connections	1358.46	1488.62	1365	1422
age	0.04	0.03	1.19	0.23	Personal Connections	1358.46	1488.62	1365	1422
educ2	3.00	3.40	0.88	0.38	Personal Connections	1358.46	1488.62	1365	1422
educ3	-0.09	3.96	-0.02	0.98	Personal Connections	1358.46	1488.62	1365	1422
educ4	1.87	3.34	0.56	0.58	Personal Connections	1358.46	1488.62	1365	1422
educ5	-12.05	898.99	-0.01	0.99	Personal Connections	1358.46	1488.62	1365	1422
educ6	2.32	3.37	0.69	0.49	Personal Connections	1358.46	1488.62	1365	1422
empl2	-0.32	1.45	-0.22	0.83	Personal Connections	1358.46	1488.62	1365	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl3	0.49	0.97	0.51	0.61	Personal Connections	1358.46	1488.62	1365	1422
empl4	-0.82	1.27	-0.65	0.52	Personal Connections	1358.46	1488.62	1365	1422
empl5	-2.25	1.28	-1.76	0.08	Personal Connections	1358.46	1488.62	1365	1422
empl6	-4.50	3.53	-1.28	0.20	Personal Connections	1358.46	1488.62	1365	1422
empl7	0.03	1.40	0.02	0.98	Personal Connections	1358.46	1488.62	1365	1422
empl8	-15.09	639.07	-0.02	0.98	Personal Connections	1358.46	1488.62	1365	1422
empl9	-1.31	3.35	-0.39	0.70	Personal Connections	1358.46	1488.62	1365	1422
empl10	-0.23	1.75	-0.13	0.89	Personal Connections	1358.46	1488.62	1365	1422
empl11	-4.92	3.55	-1.38	0.17	Personal Connections	1358.46	1488.62	1365	1422
marr_stat2	-0.79	1.28	-0.62	0.53	Personal Connections	1358.46	1488.62	1365	1422
marr_stat3	1.50	1.02	1.47	0.14	Personal Connections	1358.46	1488.62	1365	1422
marr_stat4	2.08	1.05	1.98	0.05	Personal Connections	1358.46	1488.62	1365	1422
marr_stat5	-14.62	493.46	-0.03	0.98	Personal Connections	1358.46	1488.62	1365	1422
marr_stat6	1.67	0.90	1.86	0.06	Personal Connections	1358.46	1488.62	1365	1422
average_income	0.00	0.00	1.38	0.17	Personal Connections	1358.46	1488.62	1365	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size2	0.35	0.93	0.37	0.71	Personal Connections	1358.46	1488.62	1365	1422
location_size3	-0.35	1.03	-0.34	0.73	Personal Connections	1358.46	1488.62	1365	1422
location_size4	0.36	0.97	0.37	0.71	Personal Connections	1358.46	1488.62	1365	1422
location_size5	1.59	0.91	1.75	0.08	Personal Connections	1358.46	1488.62	1365	1422
famil_numb	0.83	0.28	2.99	0.00	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:sex2	0.76	0.61	1.25	0.21	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:age	-0.02	0.03	-0.64	0.52	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:educ2	-3.53	3.43	-1.03	0.30	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:educ3	-0.54	4.00	-0.13	0.89	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:educ4	-2.25	3.37	-0.67	0.50	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:educ5	11.74	898.99	0.01	0.99	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:educ6	-3.09	3.40	-0.91	0.36	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl2	1.04	1.53	0.68	0.50	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl3	-0.28	1.06	-0.26	0.80	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl4	0.68	1.35	0.50	0.61	Personal Connections	1358.46	1488.62	1365	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:empl5	2.15	1.35	1.59	0.11	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl6	3.36	3.61	0.93	0.35	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl7	0.40	1.48	0.27	0.79	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl8	15.67	639.07	0.02	0.98	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl9	1.89	3.39	0.56	0.58	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl10	0.55	1.82	0.30	0.76	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:empl11	4.67	3.64	1.28	0.20	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:marr_stat2	0.81	1.34	0.60	0.55	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:marr_stat3	-1.81	1.06	-1.72	0.09	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:marr_stat4	-2.20	1.08	-2.03	0.04	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:marr_stat5					Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:marr_stat6	-1.56	0.93	-1.67	0.09	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:average_income	-0.00	0.00	-1.13	0.26	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:location_size2	-0.33	0.98	-0.34	0.73	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:location_size3	0.25	1.08	0.23	0.81	Personal Connections	1358.46	1488.62	1365	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:location_size4	-0.29	1.02	-0.28	0.78	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:location_size5	-1.50	0.96	-1.57	0.12	Personal Connections	1358.46	1488.62	1365	1422
personconnect_d1:famil.numb	-0.74	0.29	-2.58	0.01	Personal Connections	1358.46	1488.62	1365	1422
(Intercept)	-1.59	1.25	-1.28	0.20	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1	-1.88	1.56	-1.21	0.23	Individual Wealth	1359.67	1503.19	1364	1422
sex2	0.51	0.26	1.96	0.05	Individual Wealth	1359.67	1503.19	1364	1422
age	0.04	0.01	3.06	0.00	Individual Wealth	1359.67	1503.19	1364	1422
educ2	-1.83	0.60	-3.06	0.00	Individual Wealth	1359.67	1503.19	1364	1422
educ3	-1.62	0.82	-1.98	0.05	Individual Wealth	1359.67	1503.19	1364	1422
educ4	-2.02	0.55	-3.71	0.00	Individual Wealth	1359.67	1503.19	1364	1422
educ5	-16.78	735.27	-0.02	0.98	Individual Wealth	1359.67	1503.19	1364	1422
educ6	-2.41	0.59	-4.11	0.00	Individual Wealth	1359.67	1503.19	1364	1422
empl2	1.18	0.75	1.58	0.11	Individual Wealth	1359.67	1503.19	1364	1422
empl3	1.09	0.63	1.74	0.08	Individual Wealth	1359.67	1503.19	1364	1422
empl4	0.88	0.68	1.29	0.20	Individual Wealth	1359.67	1503.19	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl5	-0.18	0.66	-0.27	0.79	Individual Wealth	1359.67	1503.19	1364	1422
empl6	-14.26	599.56	-0.02	0.98	Individual Wealth	1359.67	1503.19	1364	1422
empl7	0.37	0.67	0.56	0.58	Individual Wealth	1359.67	1503.19	1364	1422
empl8	1.60	0.88	1.82	0.07	Individual Wealth	1359.67	1503.19	1364	1422
empl9	1.22	0.90	1.36	0.17	Individual Wealth	1359.67	1503.19	1364	1422
empl10	-0.61	0.90	-0.68	0.50	Individual Wealth	1359.67	1503.19	1364	1422
empl11	-1.00	1.59	-0.63	0.53	Individual Wealth	1359.67	1503.19	1364	1422
marr_stat2	-0.21	0.64	-0.32	0.75	Individual Wealth	1359.67	1503.19	1364	1422
marr_stat3	-0.16	0.41	-0.38	0.70	Individual Wealth	1359.67	1503.19	1364	1422
marr_stat4	-1.12	0.49	-2.29	0.02	Individual Wealth	1359.67	1503.19	1364	1422
marr_stat5	-14.53	1482.03	-0.01	0.99	Individual Wealth	1359.67	1503.19	1364	1422
marr_stat6	-0.02	0.39	-0.06	0.95	Individual Wealth	1359.67	1503.19	1364	1422
average_income	0.00	0.00	0.31	0.76	Individual Wealth	1359.67	1503.19	1364	1422
location_size2	-0.66	0.46	-1.45	0.15	Individual Wealth	1359.67	1503.19	1364	1422
location_size3	-0.77	0.48	-1.61	0.11	Individual Wealth	1359.67	1503.19	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size4	-1.00	0.47	-2.12	0.03	Individual Wealth	1359.67	1503.19	1364	1422
location_size5	-0.39	0.46	-0.83	0.40	Individual Wealth	1359.67	1503.19	1364	1422
famil_numb	0.18	0.11	1.62	0.10	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:sex2	-0.01	0.32	-0.04	0.97	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:age	-0.02	0.02	-1.53	0.13	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:educ2	2.30	0.82	2.79	0.01	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:educ3	1.73	1.10	1.57	0.12	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:educ4	2.61	0.76	3.41	0.00	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:educ5	17.37	735.27	0.02	0.98	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:educ6	2.62	0.82	3.22	0.00	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl2	-0.48	0.90	-0.53	0.60	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl3	-0.90	0.76	-1.18	0.24	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl4	-1.16	0.84	-1.38	0.17	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl5	-0.15	0.80	-0.18	0.85	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl6	13.47	599.56	0.02	0.98	Individual Wealth	1359.67	1503.19	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:empl7	-0.05	0.83	-0.06	0.95	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl8	-1.49	1.09	-1.37	0.17	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl9	-1.08	1.07	-1.01	0.31	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl10	0.88	1.04	0.84	0.40	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:empl11	0.94	1.77	0.53	0.60	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:marr_stat2	0.32	0.78	0.41	0.68	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:marr_stat3	0.09	0.52	0.17	0.87	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:marr_stat4	1.67	0.57	2.93	0.00	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:marr_stat5	-0.61	1820.98	-0.00	1.00	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:marr_stat6	0.32	0.47	0.67	0.50	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:average_income	0.00	0.00	0.33	0.74	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:location_size2	0.77	0.59	1.32	0.19	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:location_size3	0.67	0.62	1.09	0.27	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:location_size4	1.15	0.61	1.90	0.06	Individual Wealth	1359.67	1503.19	1364	1422
indivwealth_d1:location_size5	0.60	0.60	1.01	0.31	Individual Wealth	1359.67	1503.19	1364	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:famil_numb	-0.07	0.14	-0.54	0.59	Individual Wealth	1359.67	1503.19	1364	1422

Table 6: Average Marginal Contrasts: UR voters vs other

term	contrast	estimate	p.value	s.value	conf low	conf high	predicted lo	predicted hi	predicted	model
Infrastructural development (1)	ln(odds(1) odds(0))	0.95	0.73	0.45	0.69	1.29	0.59	0.64	0.64	UR voters vs other parties
Social support (1)	ln(odds(1) odds(0))	0.65	0.02	5.91	0.45	0.92	0.50	0.38	0.38	UR voters vs other parties
Economic development (1)	ln(odds(1) odds(0))	0.94	0.70	0.51	0.67	1.31	0.61	0.51	0.51	UR voters vs other parties
Personal connections (1)	ln(odds(1) odds(0))	1.61	0.01	6.36	1.11	2.33	0.28	0.48	0.48	UR voters vs other parties
Individual wealth (1)	ln(odds(1) odds(0))	1.06	0.67	0.57	0.80	1.42	0.24	0.27	0.27	UR voters vs other parties
Infrastructural development (1)	ln(odds(1) odds(0))	1.05	0.73	0.45	0.80	1.38	0.80	0.69	0.69	UR voters vs non-voters
Social support (1)	ln(odds(1) odds(0))	0.63	0.01	7.60	0.46	0.87	0.60	0.69	0.69	UR voters vs non-voters
Economic development (1)	ln(odds(1) odds(0))	0.90	0.47	1.09	0.67	1.21	0.23	0.31	0.31	UR voters vs non-voters
Personal connections (1)	ln(odds(1) odds(0))	1.11	0.53	0.90	0.79	1.57	0.73	0.52	0.52	UR voters vs non-voters
Individual wealth (1)	ln(odds(1) odds(0))	1.28	0.04	4.82	1.02	1.61	0.44	0.44	0.44	UR voters vs non-voters

Table 7: Average Marginal Contrasts: UR core and swing voters

term	contrast	estimate	p.value	s.value	conf low	conf high	predicted lo	predicted hi	predicted	model
Infrastructural development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.57	0.01	7.15	0.37	0.86	0.35	0.42	0.42	UR core vs swing voters
Social support (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.60	0.04	4.65	0.37	0.98	0.72	0.00	0.00	UR core vs swing voters
Economic development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.97	0.89	0.18	0.63	1.49	0.58	0.24	0.24	UR core vs swing voters
Personal connections (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	3.48	0.01	6.16	1.29	9.40	0.17	0.41	0.41	UR core vs swing voters
Individual wealth (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.81	0.00	8.73	1.23	2.65	0.06	0.54	0.54	UR core vs swing voters
Infrastructural development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.24	0.17	2.59	0.91	1.68	0.27	0.28	0.28	UR swing vs none/other
Social support (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.75	0.10	3.29	0.53	1.06	0.15	0.19	0.19	UR swing vs none/other
Economic development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.01	0.97	0.05	0.71	1.42	0.15	0.23	0.23	UR swing vs none/other
Personal connections (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.90	0.61	0.70	0.61	1.34	0.25	0.20	0.20	UR swing vs none/other
Individual wealth (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.83	0.18	2.48	0.63	1.09	0.32	0.28	0.28	UR swing vs none/other
Infrastructural development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.74	0.10	3.32	0.51	1.06	0.33	0.45	0.45	UR core vs none/other
Social support (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.54	0.01	6.43	0.34	0.87	0.33	0.24	0.24	UR core vs none/other
Economic development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.87	0.48	1.05	0.60	1.27	0.07	0.08	0.08	UR core vs none/other
Personal connections (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	2.37	0.05	4.19	0.98	5.72	0.15	0.23	0.23	UR core vs none/other
Individual wealth (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.33	0.13	2.98	0.92	1.91	0.04	0.13	0.13	UR core vs none/other

## E Model Results: with inducement

Table 8: GLM model: UR voters vs other parties + Inducement interaction

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-2.71	1.01	-2.68	0.01	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1	1.65	2.00	0.83	0.41	Infrastructural development + Inducement	1134.37	1264.59	858	918
sex2	0.75	0.20	3.69	0.00	Infrastructural development + Inducement	1134.37	1264.59	858	918
age	0.03	0.01	2.82	0.00	Infrastructural development + Inducement	1134.37	1264.59	858	918
educ2	0.32	0.58	0.55	0.58	Infrastructural development + Inducement	1134.37	1264.59	858	918
educ3	-0.58	0.69	-0.83	0.40	Infrastructural development + Inducement	1134.37	1264.59	858	918
educ4	0.27	0.54	0.50	0.62	Infrastructural development + Inducement	1134.37	1264.59	858	918
educ5	-1.94	0.98	-1.98	0.05	Infrastructural development + Inducement	1134.37	1264.59	858	918
educ6	0.13	0.57	0.23	0.82	Infrastructural development + Inducement	1134.37	1264.59	858	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	-0.12	0.64	-0.19	0.85	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl3	0.59	0.52	1.14	0.26	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl4	-0.20	0.55	-0.37	0.71	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl5	0.12	0.54	0.22	0.83	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl6	0.32	1.70	0.19	0.85	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl7	0.41	0.58	0.71	0.48	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl8	0.72	0.70	1.03	0.30	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl9	1.42	0.69	2.05	0.04	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl10	-0.28	0.79	-0.35	0.73	Infrastructural development + Inducement	1134.37	1264.59	858	918
empl11	-0.17	1.19	-0.14	0.89	Infrastructural development + Inducement	1134.37	1264.59	858	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-0.03	0.69	-0.05	0.96	Infrastructural development + Inducement	1134.37	1264.59	858	918
marr_stat3	-0.28	0.29	-0.96	0.34	Infrastructural development + Inducement	1134.37	1264.59	858	918
marr_stat4	-0.22	0.28	-0.78	0.44	Infrastructural development + Inducement	1134.37	1264.59	858	918
marr_stat5	-15.09	972.64	-0.02	0.99	Infrastructural development + Inducement	1134.37	1264.59	858	918
marr_stat6	0.43	0.32	1.34	0.18	Infrastructural development + Inducement	1134.37	1264.59	858	918
average_income	0.00	0.00	1.13	0.26	Infrastructural development + Inducement	1134.37	1264.59	858	918
location_size2	0.01	0.35	0.02	0.98	Infrastructural development + Inducement	1134.37	1264.59	858	918
location_size3	-0.38	0.37	-1.02	0.31	Infrastructural development + Inducement	1134.37	1264.59	858	918
location_size4	-0.47	0.37	-1.29	0.20	Infrastructural development + Inducement	1134.37	1264.59	858	918
location_size5	-0.10	0.37	-0.28	0.78	Infrastructural development + Inducement	1134.37	1264.59	858	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.09	0.09	0.96	0.34	Infrastructural development + Inducement	1134.37	1264.59	858	918
elect_induc	-0.59	0.37	-1.58	0.11	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:sex2	0.22	0.41	0.54	0.59	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:age	-0.02	0.02	-0.77	0.44	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:educ2	-0.36	1.02	-0.35	0.73	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:educ3	-0.03	1.23	-0.02	0.98	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:educ4	-0.73	0.95	-0.77	0.44	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:educ5	-13.70	979.07	-0.01	0.99	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:educ6	-1.25	1.03	-1.21	0.23	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl2	0.36	1.22	0.30	0.77	Infrastructural development + Inducement	1134.37	1264.59	858	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:empl3	-1.24	0.99	-1.25	0.21	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl4	-1.11	1.06	-1.05	0.30	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl5	-1.12	1.01	-1.10	0.27	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl6	-14.61	1528.04	-0.01	0.99	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl7	-1.51	1.06	-1.42	0.16	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl8	0.46	1.35	0.34	0.73	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl9	-2.66	1.44	-1.85	0.07	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl10	-1.07	1.45	-0.74	0.46	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:empl11	14.88	1528.04	0.01	0.99	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:marr_stat2	-1.53	1.11	-1.38	0.17	Infrastructural development + Inducement	1134.37	1264.59	858	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:marr_stat3	-0.20	0.60	-0.33	0.74	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:marr_stat4	-0.63	0.61	-1.04	0.30	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:marr_stat5	0.81	1811.34	0.00	1.00	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:marr_stat6	-1.57	0.71	-2.21	0.03	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:average_income	0.00	0.00	1.44	0.15	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:location_size2	0.89	0.71	1.26	0.21	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:location_size3	0.96	0.74	1.31	0.19	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:location_size4	1.49	0.70	2.13	0.03	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:location_size5	0.89	0.72	1.24	0.22	Infrastructural development + Inducement	1134.37	1264.59	858	918
infrastr_d1:famil numb	-0.10	0.18	-0.56	0.58	Infrastructural development + Inducement	1134.37	1264.59	858	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:elect_induc	0.92	0.77	1.20	0.23	Infrastructural development + Inducement Social Support+ Inducement Social	1134.37	1264.59	858	918
(Intercept)	-1.29	0.87	-1.49	0.14	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1	-2.43	2.72	-0.89	0.37	Support+ Inducement Social	1100.35	1237.02	860	918
sex2	0.58	0.18	3.27	0.00	Support+ Inducement Social	1100.35	1237.02	860	918
age	0.02	0.01	2.53	0.01	Support+ Inducement Social	1100.35	1237.02	860	918
educ2	0.10	0.48	0.21	0.83	Support+ Inducement Social	1100.35	1237.02	860	918
educ3	-0.36	0.59	-0.61	0.54	Support+ Inducement Social	1100.35	1237.02	860	918
educ4	-0.30	0.43	-0.71	0.48	Support+ Inducement Social	1100.35	1237.02	860	918
educ5	-1.24	0.85	-1.46	0.15	Support+ Inducement Social	1100.35	1237.02	860	918
educ6	-0.12	0.45	-0.25	0.80	Support+ Inducement	1100.35	1237.02	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	0.33	0.51	0.65	0.52	Social Support+ Inducement	1100.35	1237.02	860	918
empl3	-0.24	0.41	-0.59	0.56	Social Support+ Inducement	1100.35	1237.02	860	918
empl4	-0.73	0.46	-1.60	0.11	Social Support+ Inducement	1100.35	1237.02	860	918
empl5	-0.48	0.41	-1.17	0.24	Social Support+ Inducement	1100.35	1237.02	860	918
empl6	0.91	0.75	1.21	0.23	Social Support+ Inducement	1100.35	1237.02	860	918
empl7	-0.29	0.47	-0.60	0.55	Social Support+ Inducement	1100.35	1237.02	860	918
empl8	0.92	0.62	1.47	0.14	Social Support+ Inducement	1100.35	1237.02	860	918
empl9	0.03	0.72	0.05	0.96	Social Support+ Inducement	1100.35	1237.02	860	918
empl10	-0.30	0.49	-0.60	0.55	Social Support+ Inducement	1100.35	1237.02	860	918
empl11	2.31	0.83	2.78	0.01	Social Support+ Inducement	1100.35	1237.02	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
marr_stat2	-0.33	0.53	-0.62	0.54	Support+Inducement	1100.35	1237.02	860	918
					Social				
marr_stat3	0.05	0.34	0.15	0.88	Support+Inducement	1100.35	1237.02	860	918
					Social				
marr_stat4	0.05	0.25	0.22	0.82	Support+Inducement	1100.35	1237.02	860	918
					Social				
marr_stat5	-14.28	704.10	-0.02	0.98	Support+Inducement	1100.35	1237.02	860	918
					Social				
marr_stat6	0.28	0.28	0.97	0.33	Support+Inducement	1100.35	1237.02	860	918
					Social				
average_income	0.00	0.00	0.62	0.54	Support+Inducement	1100.35	1237.02	860	918
					Social				
location_size2	-0.69	0.32	-2.16	0.03	Support+Inducement	1100.35	1237.02	860	918
					Social				
location_size3	-0.30	0.33	-0.91	0.36	Support+Inducement	1100.35	1237.02	860	918
					Social				
location_size4	-0.36	0.34	-1.07	0.29	Support+Inducement	1100.35	1237.02	860	918
					Social				
location_size5	0.13	0.33	0.40	0.69	Support+Inducement	1100.35	1237.02	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.11	0.07	1.41	0.16	Support+ Inducement Social	1100.35	1237.02	860	918
elect_induc	0.34	0.28	1.23	0.22	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1:sex2	0.37	0.53	0.70	0.48	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1:age	-0.01	0.03	-0.56	0.58	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1:educ2	0.46	1.62	0.28	0.78	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1:educ3	-0.04	1.96	-0.02	0.99	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1:educ4	-0.33	1.44	-0.23	0.82	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1:educ5	-16.48	550.74	-0.03	0.98	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1:educ6	-0.63	1.45	-0.44	0.66	Support+ Inducement Social	1100.35	1237.02	860	918
socialsup_d1:empl2	-1.11	1.44	-0.77	0.44	Support+ Inducement	1100.35	1237.02	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
socialsup_d1:empl3	0.10	1.09	0.09	0.93	Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:empl4	-0.53	1.26	-0.42	0.68	Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:empl5	0.18	1.10	0.17	0.87	Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:empl6					Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:empl7	0.98	1.22	0.81	0.42	Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:empl8	-1.05	1.92	-0.55	0.58	Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:empl9	3.07	2.27	1.35	0.18	Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:empl10	-0.46	1.44	-0.32	0.75	Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:empl11	-5.55	2.36	-2.36	0.02	Support+Inducement	1100.35	1237.02	860	918
					Social				
socialsup_d1:marr_stat2	-1.71	1.75	-0.98	0.33	Support+Inducement	1100.35	1237.02	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:marr_stat3	0.20	1.01	0.19	0.85	Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:marr_stat4	0.00	0.77	0.00	1.00	Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:marr_stat5					Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:marr_stat6	-0.32	0.76	-0.42	0.68	Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:average_income	0.00	0.00	2.40	0.02	Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:location_size2	1.82	0.93	1.96	0.05	Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:location_size3	-0.07	1.01	-0.07	0.95	Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:location_size4	0.56	1.03	0.54	0.59	Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:location_size5	0.35	0.95	0.37	0.71	Social Support+ Inducement	1100.35	1237.02	860	918
socialsup_d1:famil_numb	0.46	0.25	1.85	0.06	Social Support+ Inducement	1100.35	1237.02	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
Social									
socialsup_d1:elect_induc	-2.95	1.56	-1.89	0.06	Support+ Inducement Economic Development+	1100.35	1237.02	860	918
(Intercept)	-2.99	0.98	-3.05	0.00	Inducement Economic	1091.91	1218.74	860	918
econdev_d1	3.41	2.51	1.36	0.18	Development+ Inducement Economic	1091.91	1218.74	860	918
sex2	0.71	0.19	3.71	0.00	Development+ Inducement Economic	1091.91	1218.74	860	918
age	0.02	0.01	2.01	0.05	Development+ Inducement Economic	1091.91	1218.74	860	918
educ2	0.63	0.50	1.26	0.21	Development+ Inducement Economic	1091.91	1218.74	860	918
educ3	0.38	0.59	0.64	0.52	Development+ Inducement Economic	1091.91	1218.74	860	918
educ4	0.17	0.47	0.37	0.71	Development+ Inducement Economic	1091.91	1218.74	860	918
educ5	1.40	0.98	1.43	0.15	Development+ Inducement Economic	1091.91	1218.74	860	918
educ6	0.25	0.51	0.49	0.62	Development+ Inducement	1091.91	1218.74	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	0.72	0.63	1.14	0.26	Economic Development+ Inducement	1091.91	1218.74	860	918
empl3	-0.08	0.50	-0.16	0.87	Economic Development+ Inducement	1091.91	1218.74	860	918
empl4	-0.65	0.53	-1.22	0.22	Economic Development+ Inducement	1091.91	1218.74	860	918
empl5	0.06	0.51	0.11	0.91	Economic Development+ Inducement	1091.91	1218.74	860	918
empl6	-0.74	1.31	-0.56	0.57	Economic Development+ Inducement	1091.91	1218.74	860	918
empl7	0.50	0.54	0.92	0.36	Economic Development+ Inducement	1091.91	1218.74	860	918
empl8	0.55	0.67	0.82	0.41	Economic Development+ Inducement	1091.91	1218.74	860	918
empl9	0.26	0.72	0.36	0.72	Economic Development+ Inducement	1091.91	1218.74	860	918
empl10	-0.32	0.61	-0.52	0.60	Economic Development+ Inducement	1091.91	1218.74	860	918
empl11	-0.78	0.67	-1.16	0.25	Economic Development+ Inducement	1091.91	1218.74	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-0.23	0.50	-0.47	0.64	Economic Development+ Inducement	1091.91	1218.74	860	918
marr_stat3	-0.49	0.28	-1.72	0.09	Economic Development+ Inducement	1091.91	1218.74	860	918
marr_stat4	-0.04	0.27	-0.13	0.90	Economic Development+ Inducement	1091.91	1218.74	860	918
marr_stat5	-14.77	409.62	-0.04	0.97	Economic Development+ Inducement	1091.91	1218.74	860	918
marr_stat6	-0.01	0.29	-0.02	0.98	Economic Development+ Inducement	1091.91	1218.74	860	918
average_income	0.00	0.00	1.91	0.06	Economic Development+ Inducement	1091.91	1218.74	860	918
location_size2	0.48	0.35	1.39	0.16	Economic Development+ Inducement	1091.91	1218.74	860	918
location_size3	0.20	0.34	0.60	0.55	Economic Development+ Inducement	1091.91	1218.74	860	918
location_size4	0.61	0.36	1.70	0.09	Economic Development+ Inducement	1091.91	1218.74	860	918
location_size5	0.56	0.36	1.55	0.12	Economic Development+ Inducement	1091.91	1218.74	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.20	0.08	2.42	0.02	Economic Development+ Inducement	1091.91	1218.74	860	918
elect_induc	0.35	0.33	1.05	0.29	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:sex2	0.05	0.52	0.10	0.92	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:age	0.02	0.02	0.70	0.49	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:educ2	-0.93	1.08	-0.86	0.39	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:educ3	-3.34	1.43	-2.34	0.02	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:educ4	-1.18	0.97	-1.22	0.22	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:educ5	-15.82	922.71	-0.02	0.99	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:educ6	-2.31	1.13	-2.04	0.04	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl2	-1.08	1.57	-0.69	0.49	Economic Development+ Inducement	1091.91	1218.74	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:empl3	0.90	1.31	0.69	0.49	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl4	0.17	1.40	0.12	0.90	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl5	-2.06	1.35	-1.52	0.13	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl6					Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl7	-1.24	1.41	-0.88	0.38	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl8	-2.64	1.84	-1.43	0.15	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl9	-0.37	1.89	-0.19	0.85	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl10	2.20	1.80	1.23	0.22	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:empl11	1.46	2.14	0.68	0.50	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:marr_stat2	-0.87	1.49	-0.58	0.56	Economic Development+ Inducement	1091.91	1218.74	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:marr_stat3	1.72	0.75	2.29	0.02	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:marr_stat4	-0.39	0.75	-0.53	0.60	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:marr_stat5					Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:marr_stat6	0.61	0.80	0.76	0.45	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:average_income	-0.00	0.00	-0.10	0.92	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:location_size2	-2.72	1.14	-2.39	0.02	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:location_size3	-2.30	1.18	-1.96	0.05	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:location_size4	-3.04	1.16	-2.61	0.01	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:location_size5	-2.04	1.13	-1.80	0.07	Economic Development+ Inducement	1091.91	1218.74	860	918
econdev_d1:famil_numb	0.02	0.20	0.11	0.91	Economic Development+ Inducement	1091.91	1218.74	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:elect_induc	-2.01	0.93	-2.15	0.03	Economic Development+ Inducement Personal	1091.91	1218.74	860	918
(Intercept)	-2.63	5.26	-0.50	0.62	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1	0.12	5.34	0.02	0.98	Connections+ Inducement Personal	1142.12	1256.73	860	918
sex2	1.67	1.03	1.62	0.11	Connections+ Inducement Personal	1142.12	1256.73	860	918
age	0.00	0.04	0.06	0.96	Connections+ Inducement Personal	1142.12	1256.73	860	918
educ2	3.74	2.57	1.46	0.14	Connections+ Inducement Personal	1142.12	1256.73	860	918
educ3	-2.14	3.16	-0.68	0.50	Connections+ Inducement Personal	1142.12	1256.73	860	918
educ4	0.13	2.43	0.06	0.96	Connections+ Inducement Personal	1142.12	1256.73	860	918
educ5	-15.59	2087.87	-0.01	0.99	Connections+ Inducement Personal	1142.12	1256.73	860	918
educ6	-1.04	2.58	-0.40	0.69	Connections+ Inducement	1142.12	1256.73	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	1.06	2.08	0.51	0.61	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl3	-1.18	1.36	-0.86	0.39	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl4	-2.66	1.79	-1.49	0.14	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl5	-3.11	1.88	-1.66	0.10	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl6	-0.77	1.31	-0.58	0.56	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl7	-1.85	1.70	-1.09	0.28	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl8	-19.09	704.60	-0.03	0.98	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl9	15.59	1452.37	0.01	0.99	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl10	-2.03	2.49	-0.81	0.42	Personal Connections+ Inducement	1142.12	1256.73	860	918
empl11	0.73	6.95	0.11	0.92	Personal Connections+ Inducement	1142.12	1256.73	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-15.65	703.54	-0.02	0.98	Personal Connections+ Inducement	1142.12	1256.73	860	918
marr_stat3	1.82	1.10	1.65	0.10	Personal Connections+ Inducement	1142.12	1256.73	860	918
marr_stat4	-0.31	1.29	-0.24	0.81	Personal Connections+ Inducement	1142.12	1256.73	860	918
marr_stat5	-15.51	718.65	-0.02	0.98	Personal Connections+ Inducement	1142.12	1256.73	860	918
marr_stat6	-2.04	1.70	-1.20	0.23	Personal Connections+ Inducement	1142.12	1256.73	860	918
average_income	0.00	0.00	0.53	0.60	Personal Connections+ Inducement	1142.12	1256.73	860	918
location_size2	2.36	2.54	0.93	0.35	Personal Connections+ Inducement	1142.12	1256.73	860	918
location_size3	1.45	2.53	0.57	0.57	Personal Connections+ Inducement	1142.12	1256.73	860	918
location_size4	1.33	2.39	0.56	0.58	Personal Connections+ Inducement	1142.12	1256.73	860	918
location_size5	1.36	2.42	0.56	0.57	Personal Connections+ Inducement	1142.12	1256.73	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.14	0.44	0.32	0.75	Connections+ Inducement Personal	1142.12	1256.73	860	918
elect_induc	-1.85	2.74	-0.68	0.50	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:sex2	-0.94	1.05	-0.90	0.37	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:age	0.02	0.04	0.36	0.72	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:educ2	-3.63	2.61	-1.39	0.16	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:educ3	1.90	3.21	0.59	0.55	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:educ4	-0.22	2.47	-0.09	0.93	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:educ5	15.75	2087.87	0.01	0.99	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:educ6	0.79	2.62	0.30	0.76	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl2	-0.65	2.15	-0.30	0.76	Connections+ Inducement	1142.12	1256.73	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:empl3	1.68	1.44	1.17	0.24	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl4	2.50	1.85	1.35	0.18	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl5	3.23	1.93	1.67	0.10	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl6					Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl7	2.30	1.77	1.30	0.19	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl8	20.15	704.60	0.03	0.98	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl9	-14.94	1452.37	-0.01	0.99	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl10	2.16	2.56	0.84	0.40	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:empl11	-1.09	7.01	-0.16	0.88	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:marr_stat2	15.57	703.54	0.02	0.98	Connections+ Inducement	1142.12	1256.73	860	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:marr_stat3	-1.90	1.14	-1.67	0.09	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:marr_stat4	0.21	1.32	0.16	0.87	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:marr_stat5					Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:marr_stat6	2.37	1.72	1.38	0.17	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:average_income	-0.00	0.00	-0.17	0.86	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:location_size2	-2.37	2.56	-0.92	0.36	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:location_size3	-1.44	2.55	-0.56	0.57	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:location_size4	-1.11	2.41	-0.46	0.64	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:location_size5	-0.99	2.44	-0.40	0.69	Connections+ Inducement Personal	1142.12	1256.73	860	918
personconnect_d1:famil_numb	0.02	0.44	0.03	0.97	Connections+ Inducement	1142.12	1256.73	860	918



term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	0.30	0.98	0.31	0.76	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl3	0.60	0.82	0.74	0.46	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl4	-0.21	0.91	-0.23	0.82	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl5	-0.55	0.84	-0.65	0.52	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl6	-0.52	1.25	-0.42	0.68	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl7	0.07	0.90	0.08	0.94	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl8	1.86	1.24	1.50	0.13	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl9	2.24	1.66	1.35	0.18	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl10	-1.41	1.42	-0.99	0.32	Individual Wealth+ Inducement	1118.05	1231.52	859	918
empl11	-0.52	1.84	-0.28	0.78	Individual Wealth+ Inducement	1118.05	1231.52	859	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-1.84	0.98	-1.88	0.06	Individual Wealth+ Inducement	1118.05	1231.52	859	918
marr_stat3	0.18	0.51	0.36	0.72	Individual Wealth+ Inducement	1118.05	1231.52	859	918
marr_stat4	-1.23	0.54	-2.28	0.02	Individual Wealth+ Inducement	1118.05	1231.52	859	918
marr_stat5	-12.73	1116.05	-0.01	0.99	Individual Wealth+ Inducement	1118.05	1231.52	859	918
marr_stat6	0.42	0.55	0.77	0.44	Individual Wealth+ Inducement	1118.05	1231.52	859	918
average_income	0.00	0.00	1.59	0.11	Individual Wealth+ Inducement	1118.05	1231.52	859	918
location_size2	-0.17	0.61	-0.28	0.78	Individual Wealth+ Inducement	1118.05	1231.52	859	918
location_size3	-0.73	0.63	-1.15	0.25	Individual Wealth+ Inducement	1118.05	1231.52	859	918
location_size4	-0.84	0.65	-1.28	0.20	Individual Wealth+ Inducement	1118.05	1231.52	859	918
location_size5	0.04	0.63	0.06	0.96	Individual Wealth+ Inducement	1118.05	1231.52	859	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.35	0.15	2.38	0.02	Individual Wealth+ Inducement	1118.05	1231.52	859	918
elect_induc	-1.40	0.78	-1.78	0.08	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:sex2	-0.41	0.38	-1.07	0.29	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:age	-0.01	0.02	-0.73	0.47	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:educ2	2.01	0.92	2.18	0.03	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:educ3	1.92	1.14	1.69	0.09	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:educ4	2.27	0.85	2.67	0.01	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:educ5	16.28	710.85	0.02	0.98	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:educ6	2.82	0.89	3.16	0.00	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl2	0.27	1.14	0.24	0.81	Individual Wealth+ Inducement	1118.05	1231.52	859	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:empl3	-0.08	0.94	-0.09	0.93	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl4	0.28	1.04	0.27	0.79	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl5	0.74	0.96	0.77	0.44	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl6					Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl7	0.31	1.03	0.30	0.76	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl8	-0.95	1.39	-0.68	0.49	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl9	-1.50	1.79	-0.84	0.40	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl10	1.66	1.53	1.08	0.28	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:empl11	0.49	2.03	0.24	0.81	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:marr_stat2	1.87	1.12	1.68	0.09	Individual Wealth+ Inducement	1118.05	1231.52	859	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:marr_stat3	-0.26	0.58	-0.45	0.65	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:marr_stat4	1.37	0.61	2.23	0.03	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:marr_stat5	-1.81	1225.98	-0.00	1.00	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:marr_stat6	-0.46	0.62	-0.73	0.47	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:average_income	-0.00	0.00	-0.87	0.38	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:location_size2	0.28	0.74	0.38	0.70	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:location_size3	0.74	0.76	0.97	0.33	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:location_size4	1.09	0.78	1.40	0.16	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:location_size5	0.28	0.76	0.37	0.71	Individual Wealth+ Inducement	1118.05	1231.52	859	918
indivwealth_d1:famil_numb	-0.30	0.17	-1.77	0.08	Individual Wealth+ Inducement	1118.05	1231.52	859	918

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:elect_induc	1.22	0.86	1.42	0.16	Individual Wealth+ Inducement	1118.05	1231.52	859	918

Table 9: GLM model: UR voters vs other parties + Inducement interaction

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-3.57	0.90	-3.95	0.00	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1	2.74	1.86	1.47	0.14	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
sex2	0.54	0.19	2.78	0.01	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
age	0.04	0.01	4.78	0.00	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
educ2	-0.78	0.57	-1.38	0.17	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
educ3	-0.72	0.69	-1.03	0.30	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
educ4	-0.24	0.53	-0.45	0.65	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
educ5	-1.33	0.85	-1.57	0.12	Infrastructural development + Inducement	1240.93	1497.03	1049	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	-0.26	0.56	-0.47	0.64	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl2	-0.41	0.52	-0.78	0.43	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl3	0.04	0.42	0.10	0.92	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl4	-0.37	0.45	-0.83	0.41	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl5	-0.34	0.41	-0.82	0.41	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl6	-1.01	0.86	-1.17	0.24	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl7	0.63	0.47	1.33	0.18	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl8	0.24	0.57	0.41	0.68	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl9	0.32	0.52	0.61	0.54	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
empl10	0.19	0.55	0.34	0.73	Infrastructural development + Inducement	1240.93	1497.03	1049	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-0.95	1.03	-0.93	0.35	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
marr_stat2	-0.42	0.42	-1.01	0.31	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
marr_stat3	-0.37	0.34	-1.08	0.28	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
marr_stat4	-0.08	0.28	-0.28	0.78	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
marr_stat5	-16.87	1209.60	-0.01	0.99	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
marr_stat6	-0.39	0.26	-1.52	0.13	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
average_income	0.00	0.00	2.11	0.04	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
location_size2	1.35	0.30	4.48	0.00	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
location_size3	1.44	0.33	4.33	0.00	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
location_size4	1.23	0.31	3.92	0.00	Infrastructural development + Inducement	1240.93	1497.03	1049	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	1.33	0.32	4.15	0.00	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
famil_numb	0.09	0.08	1.17	0.24	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
elect_induc	-0.35	0.41	-0.87	0.39	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:sex2	0.08	0.37	0.21	0.83	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:age	0.00	0.02	0.00	1.00	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:educ2	-1.82	1.36	-1.34	0.18	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:educ3	-1.60	1.53	-1.05	0.30	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:educ4	-2.38	1.32	-1.80	0.07	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:educ5	-17.17	827.59	-0.02	0.98	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:educ6	-2.16	1.36	-1.59	0.11	Infrastructural development + Inducement	1240.93	1497.03	1049	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:empl2	0.19	0.93	0.21	0.84	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl3	-0.66	0.77	-0.86	0.39	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl4	-0.05	0.84	-0.06	0.95	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl5	-0.24	0.78	-0.31	0.76	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl6	-14.92	786.20	-0.02	0.98	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl7	-0.85	0.88	-0.97	0.33	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl8	0.32	1.05	0.31	0.76	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl9	-0.72	1.06	-0.68	0.50	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl10	-0.65	1.09	-0.60	0.55	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:empl11	-0.60	1.69	-0.35	0.72	Infrastructural development + Inducement	1240.93	1497.03	1049	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:marr_stat2	0.30	0.84	0.36	0.72	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:marr_stat3	-0.12	0.60	-0.21	0.84	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:marr_stat4	-0.38	0.56	-0.69	0.49	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:marr_stat5	-0.42	2039.74	-0.00	1.00	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:marr_stat6	0.26	0.52	0.50	0.62	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:average_income	0.00	0.00	1.19	0.23	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:location_size2	-1.10	0.58	-1.88	0.06	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:location_size3	-1.24	0.64	-1.94	0.05	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:location_size4	-0.97	0.60	-1.63	0.10	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:location_size5	-0.78	0.60	-1.30	0.19	Infrastructural development + Inducement	1240.93	1497.03	1049	1109

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:famil_numb	0.18	0.16	1.13	0.26	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
infrastr_d1:elect_induc	0.49	0.69	0.70	0.48	Infrastructural development + Inducement	1240.93	1497.03	1049	1109
(Intercept)	-2.12	0.64	-3.34	0.00	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1	-1.44	1.66	-0.87	0.39	Social Support+ Inducement	1798.72	1985.83	1561	1621
sex2	0.48	0.14	3.44	0.00	Social Support+ Inducement	1798.72	1985.83	1561	1621
age	0.02	0.01	3.23	0.00	Social Support+ Inducement	1798.72	1985.83	1561	1621
educ2	-0.31	0.36	-0.86	0.39	Social Support+ Inducement	1798.72	1985.83	1561	1621
educ3	-0.34	0.45	-0.74	0.46	Social Support+ Inducement	1798.72	1985.83	1561	1621
educ4	-0.15	0.32	-0.46	0.65	Social Support+ Inducement	1798.72	1985.83	1561	1621
educ5	-1.62	0.64	-2.55	0.01	Social Support+ Inducement	1798.72	1985.83	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
educ6	-0.08	0.34	-0.24	0.81	Support+Inducement	1798.72	1985.83	1561	1621
empl2	0.41	0.38	1.09	0.28	Support+Inducement	1798.72	1985.83	1561	1621
empl3	-0.43	0.30	-1.40	0.16	Support+Inducement	1798.72	1985.83	1561	1621
empl4	-0.61	0.34	-1.79	0.07	Support+Inducement	1798.72	1985.83	1561	1621
empl5	-0.63	0.30	-2.11	0.04	Support+Inducement	1798.72	1985.83	1561	1621
empl6	-0.61	0.45	-1.34	0.18	Support+Inducement	1798.72	1985.83	1561	1621
empl7	-0.14	0.35	-0.39	0.70	Support+Inducement	1798.72	1985.83	1561	1621
empl8	0.70	0.46	1.50	0.13	Support+Inducement	1798.72	1985.83	1561	1621
empl9	-0.44	0.44	-0.98	0.33	Support+Inducement	1798.72	1985.83	1561	1621
empl10	-0.26	0.38	-0.69	0.49	Support+Inducement	1798.72	1985.83	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	0.73	0.44	1.64	0.10	Social Support+ Inducement	1798.72	1985.83	1561	1621
marr_stat2	-0.66	0.41	-1.61	0.11	Social Support+ Inducement	1798.72	1985.83	1561	1621
marr_stat3	-0.20	0.28	-0.72	0.47	Social Support+ Inducement	1798.72	1985.83	1561	1621
marr_stat4	0.00	0.20	0.02	0.99	Social Support+ Inducement	1798.72	1985.83	1561	1621
marr_stat5	-16.39	937.32	-0.02	0.99	Social Support+ Inducement	1798.72	1985.83	1561	1621
marr_stat6	0.06	0.20	0.30	0.76	Social Support+ Inducement	1798.72	1985.83	1561	1621
average_income	0.00	0.00	0.28	0.78	Social Support+ Inducement	1798.72	1985.83	1561	1621
location_size2	0.04	0.24	0.17	0.87	Social Support+ Inducement	1798.72	1985.83	1561	1621
location_size3	0.21	0.25	0.82	0.41	Social Support+ Inducement	1798.72	1985.83	1561	1621
location_size4	0.26	0.25	1.02	0.31	Social Support+ Inducement	1798.72	1985.83	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	0.53	0.25	2.13	0.03	Support+Inducement Social	1798.72	1985.83	1561	1621
famil_numb	0.13	0.06	2.25	0.02	Support+Inducement Social	1798.72	1985.83	1561	1621
elect_induc	0.55	0.23	2.46	0.01	Support+Inducement Social	1798.72	1985.83	1561	1621
socialsup_d1:sex2	0.56	0.38	1.50	0.13	Support+Inducement Social	1798.72	1985.83	1561	1621
socialsup_d1:age	0.01	0.02	0.33	0.74	Support+Inducement Social	1798.72	1985.83	1561	1621
socialsup_d1:educ2	0.36	0.97	0.37	0.71	Support+Inducement Social	1798.72	1985.83	1561	1621
socialsup_d1:educ3	-0.35	1.18	-0.30	0.77	Support+Inducement Social	1798.72	1985.83	1561	1621
socialsup_d1:educ4	-0.29	0.87	-0.34	0.73	Support+Inducement Social	1798.72	1985.83	1561	1621
socialsup_d1:educ5	-14.08	777.24	-0.02	0.99	Support+Inducement Social	1798.72	1985.83	1561	1621
socialsup_d1:educ6	-0.24	0.89	-0.27	0.79	Support+Inducement Social	1798.72	1985.83	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:empl2	-0.72	1.03	-0.70	0.48	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl3	0.37	0.76	0.48	0.63	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl4	0.14	0.85	0.16	0.87	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl5	0.10	0.75	0.13	0.90	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl6	-14.47	601.83	-0.02	0.98	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl7	0.10	0.85	0.12	0.91	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl8	-1.62	1.39	-1.17	0.24	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl9	1.09	1.02	1.07	0.29	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl10	0.08	0.95	0.08	0.94	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:empl11	-2.49	1.36	-1.82	0.07	Social Support+ Inducement	1798.72	1985.83	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:marr_stat2	0.83	0.88	0.94	0.35	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:marr_stat3	-0.14	0.70	-0.20	0.84	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:marr_stat4	-0.36	0.53	-0.68	0.50	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:marr_stat5	1.04	2592.79	0.00	1.00	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:marr_stat6	-0.59	0.53	-1.11	0.27	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:average_income	0.00	0.00	1.80	0.07	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:location_size2	0.37	0.60	0.61	0.54	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:location_size3	-0.37	0.67	-0.55	0.58	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:location_size4	0.28	0.64	0.44	0.66	Social Support+ Inducement	1798.72	1985.83	1561	1621
socialsup_d1:location_size5	0.05	0.62	0.08	0.94	Social Support+ Inducement	1798.72	1985.83	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
socialsup_d1:famil_numb	0.14	0.13	1.09	0.27	Support+Inducement	1798.72	1985.83	1561	1621
					Social				
socialsup_d1:elect_induc	-2.53	1.12	-2.27	0.02	Support+Inducement	1798.72	1985.83	1561	1621
(Intercept)	-3.05	0.69	-4.41	0.00	Development+Inducement	1816.87	1989.46	1561	1621
					Economic				
econdev_d1	0.61	1.68	0.36	0.72	Development+Inducement	1816.87	1989.46	1561	1621
					Economic				
sex2	0.51	0.15	3.41	0.00	Development+Inducement	1816.87	1989.46	1561	1621
					Economic				
age	0.02	0.01	3.86	0.00	Development+Inducement	1816.87	1989.46	1561	1621
					Economic				
educ2	0.24	0.36	0.68	0.50	Development+Inducement	1816.87	1989.46	1561	1621
					Economic				
educ3	0.09	0.45	0.20	0.84	Development+Inducement	1816.87	1989.46	1561	1621
					Economic				
educ4	-0.04	0.33	-0.12	0.90	Development+Inducement	1816.87	1989.46	1561	1621
					Economic				
educ5	0.94	0.71	1.33	0.18	Development+Inducement	1816.87	1989.46	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	-0.23	0.36	-0.65	0.52	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl2	0.88	0.46	1.89	0.06	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl3	0.35	0.38	0.92	0.36	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl4	0.01	0.40	0.02	0.98	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl5	0.21	0.37	0.57	0.57	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl6	-0.83	0.68	-1.22	0.22	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl7	0.84	0.40	2.11	0.04	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl8	0.41	0.51	0.80	0.42	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl9	0.54	0.47	1.15	0.25	Economic Development+ Inducement	1816.87	1989.46	1561	1621
empl10	0.39	0.46	0.85	0.39	Economic Development+ Inducement	1816.87	1989.46	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-0.17	0.52	-0.32	0.75	Economic Development+ Inducement	1816.87	1989.46	1561	1621
marr_stat2	-0.21	0.35	-0.60	0.55	Economic Development+ Inducement	1816.87	1989.46	1561	1621
marr_stat3	-0.41	0.23	-1.78	0.08	Economic Development+ Inducement	1816.87	1989.46	1561	1621
marr_stat4	0.17	0.21	0.82	0.41	Economic Development+ Inducement	1816.87	1989.46	1561	1621
marr_stat5	-15.23	508.08	-0.03	0.98	Economic Development+ Inducement	1816.87	1989.46	1561	1621
marr_stat6	0.18	0.20	0.90	0.37	Economic Development+ Inducement	1816.87	1989.46	1561	1621
average_income	0.00	0.00	1.14	0.25	Economic Development+ Inducement	1816.87	1989.46	1561	1621
location_size2	-0.11	0.26	-0.41	0.68	Economic Development+ Inducement	1816.87	1989.46	1561	1621
location_size3	-0.43	0.26	-1.67	0.10	Economic Development+ Inducement	1816.87	1989.46	1561	1621
location_size4	0.01	0.26	0.03	0.98	Economic Development+ Inducement	1816.87	1989.46	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	-0.13	0.27	-0.47	0.64	Economic Development+ Inducement	1816.87	1989.46	1561	1621
famil_numb	0.17	0.05	3.19	0.00	Economic Development+ Inducement	1816.87	1989.46	1561	1621
elect_induc	0.21	0.26	0.81	0.42	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:sex2	-0.23	0.37	-0.63	0.53	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:age	0.01	0.02	0.53	0.59	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:educ2	-1.19	0.79	-1.50	0.13	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:educ3	-1.61	1.07	-1.50	0.13	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:educ4	-0.54	0.73	-0.75	0.45	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:educ5	-15.60	661.86	-0.02	0.98	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:educ6	-0.92	0.81	-1.13	0.26	Economic Development+ Inducement	1816.87	1989.46	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:empl2	-0.38	1.14	-0.33	0.74	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl3	0.48	0.91	0.52	0.60	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl4	-0.28	0.97	-0.28	0.78	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl5	-0.87	0.91	-0.96	0.34	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl6	0.48	1.56	0.30	0.76	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl7	-0.71	0.98	-0.72	0.47	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl8	-0.36	1.20	-0.30	0.76	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl9	0.17	1.11	0.16	0.88	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl10	-0.05	1.09	-0.05	0.96	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:empl11	-1.38	1.44	-0.96	0.34	Economic Development+ Inducement	1816.87	1989.46	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:marr_stat2	0.03	0.83	0.03	0.97	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:marr_stat3	0.97	0.54	1.79	0.07	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:marr_stat4	-0.56	0.53	-1.05	0.29	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:marr_stat5	1.79	1146.18	0.00	1.00	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:marr_stat6	-0.03	0.51	-0.06	0.95	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:average_income	0.00	0.00	0.07	0.94	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:location_size2	0.05	0.66	0.08	0.94	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:location_size3	0.52	0.66	0.78	0.44	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:location_size4	0.17	0.64	0.26	0.79	Economic Development+ Inducement	1816.87	1989.46	1561	1621
econdev_d1:location_size5	0.84	0.65	1.30	0.19	Economic Development+ Inducement	1816.87	1989.46	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:famil_numb	-0.05	0.14	-0.39	0.69	Economic Development+ Inducement Economic	1816.87	1989.46	1561	1621
econdev_d1:elect_induc	-1.52	0.67	-2.25	0.02	Development+ Inducement Personal	1816.87	1989.46	1561	1621
(Intercept)	-6.84	2.97	-2.30	0.02	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1	4.00	3.05	1.31	0.19	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
sex2	0.11	0.53	0.21	0.83	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
age	0.03	0.03	1.00	0.32	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
educ2	1.76	2.01	0.87	0.38	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
educ3	-0.51	2.45	-0.21	0.83	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
educ4	0.87	1.96	0.44	0.66	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
educ5	-13.44	880.61	-0.02	0.99	Connections+ Inducement	1817.72	2010.86	1562	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Personal				
educ6	1.08	2.00	0.54	0.59	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl2	-0.60	1.34	-0.44	0.66	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl3	0.31	0.91	0.34	0.73	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl4	-1.01	1.15	-0.88	0.38	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl5	-1.97	1.12	-1.76	0.08	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl6	-4.11	3.39	-1.21	0.22	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl7	-0.12	1.23	-0.10	0.92	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl8	-15.41	619.81	-0.02	0.98	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl9	0.67	1.46	0.46	0.65	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
empl10	0.04	1.57	0.03	0.98	Connections+ Inducement	1817.72	2010.86	1562	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-5.01	3.44	-1.46	0.15	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
marr_stat2	-1.11	1.23	-0.90	0.37	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
marr_stat3	1.74	0.85	2.05	0.04	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
marr_stat4	1.62	0.85	1.90	0.06	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
marr_stat5	-15.21	478.52	-0.03	0.97	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
marr_stat6	1.25	0.81	1.56	0.12	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
average_income	0.00	0.00	2.16	0.03	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
location_size2	0.70	0.86	0.82	0.41	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
location_size3	-0.47	1.00	-0.47	0.64	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
location_size4	0.83	0.85	0.97	0.33	Connections+ Inducement	1817.72	2010.86	1562	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Personal				
location_size5	1.49	0.88	1.69	0.09	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
famil_numb	0.72	0.25	2.90	0.00	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
elect_induc	-0.55	0.95	-0.57	0.57	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:sex2	0.54	0.55	0.98	0.33	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:age	-0.00	0.03	-0.18	0.86	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:educ2	-2.05	2.05	-1.00	0.32	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:educ3	0.09	2.50	0.04	0.97	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:educ4	-1.12	1.99	-0.56	0.57	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:educ5	13.38	880.61	0.02	0.99	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:educ6	-1.50	2.03	-0.74	0.46	Connections+ Inducement	1817.72	2010.86	1562	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:empl2	1.04	1.40	0.74	0.46	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl3	-0.05	0.98	-0.05	0.96	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl4	0.95	1.21	0.79	0.43	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl5	1.99	1.18	1.69	0.09	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl6	2.73	3.47	0.79	0.43	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl7	0.60	1.29	0.47	0.64	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl8	16.19	619.81	0.03	0.98	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl9	-0.22	1.52	-0.14	0.89	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl10	0.19	1.63	0.12	0.91	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:empl11	4.49	3.51	1.28	0.20	Connections+ Inducement	1817.72	2010.86	1562	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:marr_stat2	0.83	1.28	0.65	0.52	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:marr_stat3	-2.02	0.88	-2.30	0.02	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:marr_stat4	-1.80	0.88	-2.04	0.04	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:marr_stat5					Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:marr_stat6	-1.31	0.83	-1.58	0.11	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:average_income	-0.00	0.00	-1.67	0.09	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:location_size2	-0.44	0.90	-0.49	0.62	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:location_size3	0.73	1.03	0.71	0.48	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:location_size4	-0.37	0.89	-0.42	0.67	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:location_size5	-1.03	0.92	-1.11	0.27	Connections+ Inducement	1817.72	2010.86	1562	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:famil_numb	-0.59	0.25	-2.33	0.02	Connections+ Inducement Personal	1817.72	2010.86	1562	1621
personconnect_d1:elect_induc	0.28	0.99	0.28	0.78	Connections+ Inducement Individual	1817.72	2010.86	1562	1621
(Intercept)	-2.01	1.13	-1.79	0.07	Wealth+ Inducement Individual	1789.47	2011.53	1561	1621
indivwealth_d1	-1.54	1.36	-1.14	0.26	Wealth+ Inducement Individual	1789.47	2011.53	1561	1621
sex2	0.83	0.24	3.50	0.00	Wealth+ Inducement Individual	1789.47	2011.53	1561	1621
age	0.04	0.01	3.62	0.00	Wealth+ Inducement Individual	1789.47	2011.53	1561	1621
educ2	-1.77	0.53	-3.31	0.00	Wealth+ Inducement Individual	1789.47	2011.53	1561	1621
educ3	-1.47	0.72	-2.05	0.04	Wealth+ Inducement Individual	1789.47	2011.53	1561	1621
educ4	-2.06	0.50	-4.15	0.00	Wealth+ Inducement Individual	1789.47	2011.53	1561	1621
educ5	-16.92	689.57	-0.02	0.98	Wealth+ Inducement	1789.47	2011.53	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	-2.32	0.53	-4.37	0.00	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl2	0.76	0.69	1.10	0.27	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl3	1.19	0.57	2.10	0.04	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl4	0.85	0.62	1.36	0.17	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl5	0.12	0.58	0.21	0.83	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl6	-14.48	595.03	-0.02	0.98	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl7	0.48	0.61	0.79	0.43	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl8	1.96	0.78	2.52	0.01	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl9	1.12	0.80	1.39	0.16	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
empl10	-0.67	0.84	-0.80	0.43	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-1.20	1.55	-0.78	0.44	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
marr_stat2	-0.53	0.59	-0.89	0.37	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
marr_stat3	-0.15	0.36	-0.42	0.68	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
marr_stat4	-1.10	0.40	-2.72	0.01	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
marr_stat5	-15.18	1458.79	-0.01	0.99	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
marr_stat6	-0.17	0.36	-0.47	0.64	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
average_income	0.00	0.00	1.47	0.14	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
location_size2	-0.51	0.42	-1.21	0.23	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
location_size3	-0.52	0.44	-1.17	0.24	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
location_size4	-0.90	0.44	-2.07	0.04	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	-0.15	0.43	-0.36	0.72	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
famil_numb	0.21	0.10	2.13	0.03	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
elect_induc	-1.58	0.64	-2.48	0.01	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:sex2	-0.39	0.28	-1.36	0.17	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:age	-0.02	0.01	-1.52	0.13	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:educ2	2.17	0.69	3.15	0.00	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:educ3	1.88	0.90	2.09	0.04	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:educ4	2.56	0.64	3.98	0.00	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:educ5	17.44	689.57	0.03	0.98	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:educ6	2.71	0.69	3.96	0.00	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:empl2	-0.16	0.82	-0.19	0.85	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl3	-0.89	0.67	-1.33	0.18	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl4	-0.83	0.74	-1.12	0.26	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl5	-0.18	0.69	-0.27	0.79	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl6	13.69	595.03	0.02	0.98	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl7	-0.01	0.72	-0.01	0.99	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl8	-1.44	0.93	-1.55	0.12	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl9	-0.76	0.93	-0.82	0.42	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl10	1.10	0.94	1.16	0.24	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:empl11	0.94	1.69	0.55	0.58	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:marr_stat2	0.25	0.71	0.35	0.72	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:marr_stat3	0.02	0.44	0.05	0.96	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:marr_stat4	1.41	0.47	3.00	0.00	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:marr_stat5	-0.87	1789.30	-0.00	1.00	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:marr_stat6	0.16	0.42	0.37	0.71	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:average_income	-0.00	0.00	-0.36	0.72	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:location_size2	0.95	0.53	1.80	0.07	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:location_size3	0.82	0.55	1.50	0.13	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:location_size4	1.51	0.54	2.79	0.01	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:location_size5	0.69	0.53	1.30	0.19	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:famil_numb	-0.12	0.12	-0.99	0.32	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621
indivwealth_d1:elect_induc	1.46	0.71	2.07	0.04	Individual Wealth+ Inducement	1789.47	2011.53	1561	1621

Table 10: GLM model: UR core vs swing voters + Inducement interaction

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-4.30	1.52	-2.83	0.00	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1	3.23	2.78	1.16	0.25	Infrastructural development + Inducement	553.70	640.55	448	504
sex2	0.23	0.30	0.76	0.45	Infrastructural development + Inducement	553.70	640.55	448	504
age	-0.00	0.01	-0.22	0.83	Infrastructural development + Inducement	553.70	640.55	448	504
educ2	1.27	0.76	1.67	0.10	Infrastructural development + Inducement	553.70	640.55	448	504
educ3	1.85	1.04	1.78	0.08	Infrastructural development + Inducement	553.70	640.55	448	504
educ4	0.80	0.71	1.12	0.26	Infrastructural development + Inducement	553.70	640.55	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ5	1.35	1.36	1.00	0.32	Infrastructural development + Inducement	553.70	640.55	448	504
educ6	1.26	0.75	1.69	0.09	Infrastructural development + Inducement	553.70	640.55	448	504
empl2	0.63	1.08	0.59	0.56	Infrastructural development + Inducement	553.70	640.55	448	504
empl3	1.50	0.89	1.68	0.09	Infrastructural development + Inducement	553.70	640.55	448	504
empl4	1.98	0.94	2.10	0.04	Infrastructural development + Inducement	553.70	640.55	448	504
empl5	1.70	0.90	1.89	0.06	Infrastructural development + Inducement	553.70	640.55	448	504
empl6	-15.50	2537.42	-0.01	1.00	Infrastructural development + Inducement	553.70	640.55	448	504
empl7	2.28	0.94	2.44	0.02	Infrastructural development + Inducement	553.70	640.55	448	504
empl8	1.78	1.03	1.72	0.09	Infrastructural development + Inducement	553.70	640.55	448	504
empl9	1.05	1.00	1.05	0.29	Infrastructural development + Inducement	553.70	640.55	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl10	0.63	1.15	0.55	0.58	Infrastructural development + Inducement	553.70	640.55	448	504
empl11	0.57	2.34	0.25	0.81	Infrastructural development + Inducement	553.70	640.55	448	504
marr_stat2	-0.79	0.92	-0.86	0.39	Infrastructural development + Inducement	553.70	640.55	448	504
marr_stat3	0.02	0.38	0.06	0.95	Infrastructural development + Inducement	553.70	640.55	448	504
marr_stat4	-0.69	0.42	-1.63	0.10	Infrastructural development + Inducement	553.70	640.55	448	504
marr_stat6	-0.31	0.45	-0.69	0.49	Infrastructural development + Inducement	553.70	640.55	448	504
average_income	0.00	0.00	1.64	0.10	Infrastructural development + Inducement	553.70	640.55	448	504
location_size2	1.16	0.52	2.23	0.03	Infrastructural development + Inducement	553.70	640.55	448	504
location_size3	0.98	0.56	1.76	0.08	Infrastructural development + Inducement	553.70	640.55	448	504
location_size4	0.77	0.55	1.40	0.16	Infrastructural development + Inducement	553.70	640.55	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	1.21	0.53	2.28	0.02	Infrastructural development + Inducement	553.70	640.55	448	504
famil_numb	0.02	0.13	0.14	0.89	Infrastructural development + Inducement	553.70	640.55	448	504
elect_induc	-0.69	0.62	-1.12	0.26	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:sex2	0.53	0.75	0.71	0.48	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:age	-0.03	0.03	-0.92	0.36	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:educ2	-0.41	1.50	-0.27	0.79	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:educ3	-17.95	1647.68	-0.01	0.99	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:educ4	-0.11	1.40	-0.08	0.94	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:educ5					Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:educ6	0.57	1.63	0.35	0.73	Infrastructural development + Inducement	553.70	640.55	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:empl2	-19.23	1235.57	-0.02	0.99	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl3	-3.49	1.46	-2.39	0.02	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl4	-3.70	1.62	-2.28	0.02	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl5	-2.04	1.48	-1.38	0.17	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl6					Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl7	-3.49	1.67	-2.09	0.04	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl8	-1.29	1.77	-0.73	0.47	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl9	-3.86	1.92	-2.01	0.05	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl10	-18.41	1701.99	-0.01	0.99	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:empl11	-19.84	4082.85	-0.00	1.00	Infrastructural development + Inducement	553.70	640.55	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:marr_stat2	-0.13	1.68	-0.08	0.94	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:marr_stat3	-0.03	0.89	-0.03	0.98	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:marr_stat4	0.23	0.95	0.24	0.81	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:marr_stat6	-1.21	1.07	-1.13	0.26	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:average_income	0.00	0.00	0.56	0.58	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:location_size2	-0.64	1.17	-0.55	0.59	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:location_size3	1.43	1.27	1.12	0.26	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:location_size4	1.13	1.21	0.93	0.35	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:location_size5	-0.04	1.17	-0.04	0.97	Infrastructural development + Inducement	553.70	640.55	448	504
infrastr_d1:famil_numb	-0.03	0.27	-0.10	0.92	Infrastructural development + Inducement	553.70	640.55	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:elect_induc	-1.24	1.69	-0.73	0.46	Infrastructural development + Inducement Social Support+ Inducement Social	553.70	640.55	448	504
(Intercept)	-2.44	1.27	-1.93	0.05		538.78	645.86	448	504
socialsup_d1	-7.95	1060.06	-0.01	0.99		538.78	645.86	448	504
sex2	0.02	0.29	0.06	0.95		538.78	645.86	448	504
age	0.00	0.01	0.02	0.98		538.78	645.86	448	504
educ2	0.61	0.70	0.87	0.38		538.78	645.86	448	504
educ3	0.95	0.87	1.10	0.27		538.78	645.86	448	504
educ4	0.18	0.62	0.30	0.77		538.78	645.86	448	504
educ5	0.72	1.31	0.55	0.58		538.78	645.86	448	504
educ6	1.22	0.66	1.84	0.07		538.78	645.86	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	-1.58	0.75	-2.11	0.04	Social Support+ Inducement	538.78	645.86	448	504
empl3	0.01	0.57	0.01	0.99	Social Support+ Inducement	538.78	645.86	448	504
empl4	0.14	0.65	0.22	0.83	Social Support+ Inducement	538.78	645.86	448	504
empl5	0.33	0.56	0.60	0.55	Social Support+ Inducement	538.78	645.86	448	504
empl6	-16.11	1096.57	-0.01	0.99	Social Support+ Inducement	538.78	645.86	448	504
empl7	0.45	0.65	0.69	0.49	Social Support+ Inducement	538.78	645.86	448	504
empl8	1.42	0.79	1.81	0.07	Social Support+ Inducement	538.78	645.86	448	504
empl9	-1.03	0.87	-1.19	0.24	Social Support+ Inducement	538.78	645.86	448	504
empl10	-0.84	0.74	-1.14	0.25	Social Support+ Inducement	538.78	645.86	448	504
empl11	-3.48	1.42	-2.45	0.01	Social Support+ Inducement	538.78	645.86	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-0.61	0.90	-0.68	0.50	Social Support+ Inducement	538.78	645.86	448	504
marr_stat3	-0.54	0.48	-1.12	0.26	Social Support+ Inducement	538.78	645.86	448	504
marr_stat4	-0.48	0.38	-1.26	0.21	Social Support+ Inducement	538.78	645.86	448	504
marr_stat6	-0.88	0.43	-2.08	0.04	Social Support+ Inducement	538.78	645.86	448	504
average_income	0.00	0.00	1.51	0.13	Social Support+ Inducement	538.78	645.86	448	504
location_size2	1.00	0.50	1.99	0.05	Social Support+ Inducement	538.78	645.86	448	504
location_size3	1.69	0.51	3.31	0.00	Social Support+ Inducement	538.78	645.86	448	504
location_size4	1.45	0.52	2.82	0.01	Social Support+ Inducement	538.78	645.86	448	504
location_size5	1.26	0.51	2.47	0.01	Social Support+ Inducement	538.78	645.86	448	504
famil_numb	0.07	0.12	0.57	0.57	Social Support+ Inducement	538.78	645.86	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
elect_induc	-0.13	0.44	-0.30	0.76	Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:sex2	0.23	0.98	0.24	0.81	Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:age	-0.03	0.05	-0.53	0.59	Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:educ2	-2.99	2.44	-1.23	0.22	Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:educ3	-2.64	2.79	-0.95	0.34	Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:educ4	-3.99	2.36	-1.69	0.09	Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:educ5					Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:educ6	-3.33	2.19	-1.52	0.13	Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:empl2	1.34	1656.97	0.00	1.00	Support+ Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:empl3	15.53	1060.06	0.01	0.99	Support+ Inducement	538.78	645.86	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:empl4	15.97	1060.06	0.02	0.99	Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:empl5	14.58	1060.06	0.01	0.99	Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:empl6					Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:empl7	16.04	1060.06	0.02	0.99	Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:empl8	-4.35	2791.18	-0.00	1.00	Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:empl9	13.97	1060.06	0.01	0.99	Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:empl10	16.85	1060.06	0.02	0.99	Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:empl11	6.19	2791.19	0.00	1.00	Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:marr_stat2	-15.23	1420.71	-0.01	0.99	Social Support+ Inducement	538.78	645.86	448	504
socialsup_d1:marr_stat3	1.86	1.74	1.07	0.29	Social Support+ Inducement	538.78	645.86	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
socialsup_d1:marr_stat4	1.74	1.38	1.27	0.21	Support+Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:marr_stat6	-0.93	1.59	-0.58	0.56	Support+Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:average_income	-0.00	0.00	-1.04	0.30	Support+Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:location_size2	-0.93	1.48	-0.63	0.53	Support+Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:location_size3	-1.46	1.83	-0.80	0.43	Support+Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:location_size4	-4.44	2.10	-2.11	0.04	Support+Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:location_size5	-1.72	1.59	-1.09	0.28	Support+Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:famil_numb	-0.33	0.39	-0.84	0.40	Support+Inducement	538.78	645.86	448	504
					Social				
socialsup_d1:elect_induc	-16.48	2582.05	-0.01	0.99	Support+Inducement	538.78	645.86	448	504
					Economic				
(Intercept)	-3.23	1.35	-2.39	0.02	Development+Inducement	565.77	662.61	447	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1	-1.98	3.43	-0.58	0.56	Economic Development+ Inducement	565.77	662.61	447	504
sex2	-0.34	0.29	-1.18	0.24	Economic Development+ Inducement	565.77	662.61	447	504
age	0.03	0.01	2.33	0.02	Economic Development+ Inducement	565.77	662.61	447	504
educ2	-0.01	0.65	-0.02	0.98	Economic Development+ Inducement	565.77	662.61	447	504
educ3	-0.36	0.78	-0.46	0.64	Economic Development+ Inducement	565.77	662.61	447	504
educ4	-0.13	0.61	-0.21	0.83	Economic Development+ Inducement	565.77	662.61	447	504
educ5	0.25	1.21	0.20	0.84	Economic Development+ Inducement	565.77	662.61	447	504
educ6	1.12	0.66	1.70	0.09	Economic Development+ Inducement	565.77	662.61	447	504
empl2	-2.28	1.09	-2.10	0.04	Economic Development+ Inducement	565.77	662.61	447	504
empl3	-0.25	0.72	-0.35	0.73	Economic Development+ Inducement	565.77	662.61	447	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Economic				
empl4	0.58	0.76	0.77	0.44	Development+ Inducement Economic	565.77	662.61	447	504
empl5	0.29	0.72	0.40	0.69	Development+ Inducement Economic	565.77	662.61	447	504
empl6	-14.33	825.64	-0.02	0.99	Development+ Inducement Economic	565.77	662.61	447	504
empl7	-0.23	0.76	-0.30	0.76	Development+ Inducement Economic	565.77	662.61	447	504
empl8	-0.88	0.98	-0.89	0.37	Development+ Inducement Economic	565.77	662.61	447	504
empl9	-0.82	0.91	-0.89	0.37	Development+ Inducement Economic	565.77	662.61	447	504
empl10	-1.01	1.00	-1.01	0.31	Development+ Inducement Economic	565.77	662.61	447	504
empl11	0.15	0.99	0.15	0.88	Development+ Inducement Economic	565.77	662.61	447	504
marr_stat2	-0.50	0.77	-0.65	0.52	Development+ Inducement Economic	565.77	662.61	447	504
marr_stat3	0.02	0.39	0.04	0.97	Development+ Inducement	565.77	662.61	447	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Economic				
marr_stat4	-0.26	0.37	-0.71	0.48	Development+ Inducement Economic	565.77	662.61	447	504
marr_stat6	-0.55	0.40	-1.37	0.17	Development+ Inducement Economic	565.77	662.61	447	504
average_income	0.00	0.00	0.86	0.39	Development+ Inducement Economic	565.77	662.61	447	504
location_size2	1.19	0.51	2.34	0.02	Development+ Inducement Economic	565.77	662.61	447	504
location_size3	1.32	0.53	2.49	0.01	Development+ Inducement Economic	565.77	662.61	447	504
location_size4	1.20	0.51	2.34	0.02	Development+ Inducement Economic	565.77	662.61	447	504
location_size5	1.16	0.53	2.17	0.03	Development+ Inducement Economic	565.77	662.61	447	504
famil_numb	0.16	0.11	1.46	0.15	Development+ Inducement Economic	565.77	662.61	447	504
elect_induc	0.33	0.46	0.72	0.47	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:sex2	1.81	0.88	2.05	0.04	Development+ Inducement	565.77	662.61	447	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:age	-0.03	0.03	-0.82	0.41	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:educ2	1.64	1.49	1.11	0.27	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:educ3	2.47	2.25	1.10	0.27	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:educ4	1.52	1.34	1.14	0.26	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:educ5					Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:educ6	-0.40	1.59	-0.25	0.80	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:empl2	1.53	2.79	0.55	0.58	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:empl3	-0.24	1.89	-0.13	0.90	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:empl4	-3.32	2.43	-1.37	0.17	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:empl5	0.66	1.96	0.34	0.74	Economic Development+ Inducement	565.77	662.61	447	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:empl6	-1.25	1713.71	-0.00	1.00	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:empl7	0.23	2.17	0.11	0.91	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:empl8	1.94	2.54	0.76	0.45	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:empl9	-0.39	2.24	-0.17	0.86	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:empl10	2.19	2.23	0.99	0.32	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:empl11	-21.90	1501.71	-0.01	0.99	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:marr_stat2	-15.07	757.97	-0.02	0.98	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:marr_stat3	0.68	0.89	0.76	0.45	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:marr_stat4	0.87	1.07	0.81	0.42	Development+ Inducement Economic	565.77	662.61	447	504
econdev_d1:marr_stat6	-0.02	1.12	-0.02	0.98	Development+ Inducement	565.77	662.61	447	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:average_income	0.00	0.00	1.87	0.06	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:location_size2	-0.76	1.31	-0.58	0.56	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:location_size3	-0.57	1.37	-0.42	0.68	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:location_size4	0.57	1.38	0.41	0.68	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:location_size5	0.30	1.27	0.24	0.81	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:famil_numb	-0.10	0.30	-0.33	0.74	Economic Development+ Inducement	565.77	662.61	447	504
econdev_d1:elect_induc	-1.69	1.55	-1.10	0.27	Personal Development+ Inducement	565.77	662.61	447	504
(Intercept)	-1.53	0.38	-4.01	0.00	Personal Connections+ Inducement	660.82	674.79	500	504
personconnect_d1	1.19	0.39	3.02	0.00	Personal Connections+ Inducement	660.82	674.79	500	504
elect_induc	-13.31	610.50	-0.02	0.98	Personal Connections+ Inducement	660.82	674.79	500	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:elect_induc	13.07	610.50	0.02	0.98	Personal Connections+ Inducement Individual Wealth+	660.82	674.79	500	504
(Intercept)	-7.43	2.63	-2.82	0.00	Inducement Individual Wealth+ Inducement Individual Wealth+	584.75	671.04	448	504
indivwealth_d1	5.48	2.99	1.83	0.07	Individual Wealth+ Inducement Individual Wealth+	584.75	671.04	448	504
sex2	1.56	0.58	2.70	0.01	Individual Wealth+ Inducement Individual Wealth+	584.75	671.04	448	504
age	0.00	0.02	0.19	0.85	Individual Wealth+ Inducement Individual Wealth+	584.75	671.04	448	504
educ2	0.03	0.99	0.03	0.97	Individual Wealth+ Inducement Individual Wealth+	584.75	671.04	448	504
educ3	-0.16	1.31	-0.12	0.90	Individual Wealth+ Inducement Individual Wealth+	584.75	671.04	448	504
educ4	-0.67	0.89	-0.74	0.46	Individual Wealth+ Inducement Individual Wealth+	584.75	671.04	448	504
educ5	-0.52	1.07	-0.48	0.63	Individual Wealth+ Inducement Individual Wealth+	584.75	671.04	448	504
educ6	0.58	1.01	0.58	0.56	Individual Wealth+ Inducement	584.75	671.04	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	-15.27	844.37	-0.02	0.99	Individual Wealth+ Inducement	584.75	671.04	448	504
empl3	1.43	1.44	1.00	0.32	Individual Wealth+ Inducement	584.75	671.04	448	504
empl4	0.81	1.65	0.49	0.62	Individual Wealth+ Inducement	584.75	671.04	448	504
empl5	2.73	1.56	1.75	0.08	Individual Wealth+ Inducement	584.75	671.04	448	504
empl6	-15.21	1166.87	-0.01	0.99	Individual Wealth+ Inducement	584.75	671.04	448	504
empl7	2.41	1.74	1.39	0.17	Individual Wealth+ Inducement	584.75	671.04	448	504
empl8	2.96	1.81	1.63	0.10	Individual Wealth+ Inducement	584.75	671.04	448	504
empl9	0.64	1.74	0.37	0.71	Individual Wealth+ Inducement	584.75	671.04	448	504
empl10	-1.65	3.35	-0.49	0.62	Individual Wealth+ Inducement	584.75	671.04	448	504
empl11	-19.67	3125.67	-0.01	0.99	Individual Wealth+ Inducement	584.75	671.04	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-1.42	1.66	-0.85	0.39	Individual Wealth+ Inducement	584.75	671.04	448	504
marr_stat3	0.12	0.63	0.19	0.85	Individual Wealth+ Inducement	584.75	671.04	448	504
marr_stat4	-0.12	0.88	-0.13	0.89	Individual Wealth+ Inducement	584.75	671.04	448	504
marr_stat6	-0.62	0.90	-0.68	0.50	Individual Wealth+ Inducement	584.75	671.04	448	504
average_income	0.00	0.00	2.78	0.01	Individual Wealth+ Inducement	584.75	671.04	448	504
location_size2	1.42	1.01	1.40	0.16	Individual Wealth+ Inducement	584.75	671.04	448	504
location_size3	1.44	1.04	1.39	0.17	Individual Wealth+ Inducement	584.75	671.04	448	504
location_size4	1.49	1.04	1.44	0.15	Individual Wealth+ Inducement	584.75	671.04	448	504
location_size5	1.77	1.00	1.77	0.08	Individual Wealth+ Inducement	584.75	671.04	448	504
famil_numb	0.31	0.23	1.39	0.17	Individual Wealth+ Inducement	584.75	671.04	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
elect_induc	-1.75	1.78	-0.98	0.33	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:sex2	-1.80	0.65	-2.77	0.01	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:age	0.01	0.03	0.46	0.65	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:educ2	-0.50	1.26	-0.40	0.69	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:educ3	0.82	1.65	0.50	0.62	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:educ4	0.38	1.16	0.33	0.74	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:educ5					Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:educ6	-0.24	1.26	-0.19	0.85	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl2	14.58	844.37	0.02	0.99	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl3	-1.28	1.60	-0.80	0.42	Individual Wealth+ Inducement	584.75	671.04	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:empl4	-0.31	1.81	-0.17	0.87	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl5	-2.23	1.70	-1.31	0.19	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl6					Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl7	-2.23	1.88	-1.19	0.24	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl8	-2.36	2.02	-1.16	0.24	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl9	-0.01	1.95	-0.00	1.00	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl10	2.06	3.45	0.60	0.55	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:empl11	19.16	3125.67	0.01	1.00	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:marr_stat2	0.36	1.88	0.19	0.85	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:marr_stat3	-0.27	0.74	-0.37	0.71	Individual Wealth+ Inducement	584.75	671.04	448	504

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:marr_stat4	-0.39	0.96	-0.40	0.69	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:marr_stat6	-0.17	1.00	-0.17	0.86	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:average_income	-0.00	0.00	-2.57	0.01	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:location_size2	-0.58	1.19	-0.49	0.63	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:location_size3	-0.43	1.23	-0.35	0.72	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:location_size4	-0.19	1.22	-0.16	0.87	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:location_size5	-0.89	1.19	-0.75	0.45	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:famil_numb	-0.29	0.26	-1.14	0.25	Individual Wealth+ Inducement	584.75	671.04	448	504
indivwealth_d1:elect_induc	1.78	1.87	0.95	0.34	Individual Wealth+ Inducement	584.75	671.04	448	504

Table 11: GLM model: UR swing voters vs other parties/non-voters + Inducement interaction

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-2.77	0.84	-3.29	0.00	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr.d1	0.91	1.58	0.58	0.56	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
sex2	0.50	0.19	2.62	0.01	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
age	0.03	0.01	3.57	0.00	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
educ2	-0.91	0.49	-1.88	0.06	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
educ3	-1.78	0.70	-2.53	0.01	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
educ4	-0.32	0.43	-0.75	0.45	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
educ5	-1.78	0.84	-2.13	0.03	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
educ6	-0.54	0.47	-1.16	0.25	Infrastructural development + Inducement	1378.77	1507.64	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	-0.45	0.50	-0.90	0.37	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl3	-0.29	0.40	-0.72	0.47	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl4	-1.15	0.44	-2.62	0.01	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl5	-0.63	0.40	-1.57	0.12	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl6	-0.75	0.84	-0.90	0.37	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl7	-0.32	0.44	-0.71	0.48	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl8	-0.25	0.55	-0.45	0.65	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl9	0.34	0.51	0.66	0.51	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl10	-0.00	0.52	-0.00	1.00	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
empl11	-0.86	1.05	-0.82	0.41	Infrastructural development + Inducement	1378.77	1507.64	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	0.33	0.43	0.78	0.44	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
marr_stat3	-0.34	0.31	-1.07	0.28	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
marr_stat4	0.15	0.27	0.57	0.57	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
marr_stat5	-15.35	921.48	-0.02	0.99	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
marr_stat6	0.06	0.28	0.22	0.83	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
average_income	0.00	0.00	0.12	0.91	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
location_size2	0.31	0.31	1.01	0.31	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
location_size3	0.24	0.33	0.73	0.46	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
location_size4	0.25	0.32	0.79	0.43	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
location_size5	0.26	0.33	0.80	0.42	Infrastructural development + Inducement	1378.77	1507.64	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.13	0.08	1.61	0.11	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
elect_induc	-0.17	0.35	-0.50	0.62	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:sex2	0.09	0.34	0.25	0.80	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:age	-0.01	0.02	-0.48	0.63	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:educ2	-0.04	0.91	-0.04	0.97	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:educ3	1.06	1.13	0.94	0.35	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:educ4	-0.71	0.83	-0.85	0.39	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:educ5	-14.51	759.05	-0.02	0.98	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:educ6	-0.85	0.89	-0.96	0.34	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl2	1.38	0.92	1.50	0.13	Infrastructural development + Inducement	1378.77	1507.64	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:empl3	0.11	0.78	0.14	0.89	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl4	0.93	0.83	1.12	0.26	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl5	-0.04	0.80	-0.05	0.96	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl6	-14.29	780.18	-0.02	0.99	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl7	0.19	0.84	0.23	0.82	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl8	0.70	1.06	0.66	0.51	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl9	-0.11	1.05	-0.11	0.91	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl10	-0.12	1.02	-0.12	0.91	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:empl11	0.73	1.71	0.43	0.67	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:marr_stat2	-0.53	0.79	-0.68	0.50	Infrastructural development + Inducement	1378.77	1507.64	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:marr_stat3	-0.20	0.54	-0.37	0.71	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:marr_stat4	-0.79	0.53	-1.48	0.14	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:marr_stat5	-0.12	1651.35	-0.00	1.00	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:marr_stat6	-0.16	0.52	-0.31	0.76	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:average_income	0.00	0.00	1.18	0.24	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:location_size2	0.07	0.55	0.13	0.89	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:location_size3	-0.35	0.60	-0.59	0.56	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:location_size4	-0.12	0.56	-0.22	0.83	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:location_size5	0.04	0.57	0.07	0.94	Infrastructural development + Inducement	1378.77	1507.64	1362	1422
infrastr_d1:famil_numb	-0.04	0.14	-0.28	0.78	Infrastructural development + Inducement	1378.77	1507.64	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:elect_induc	0.63	0.62	1.03	0.31	Infrastructural development + Inducement Social Support+ Inducement Social	1378.77	1507.64	1362	1422
(Intercept)	-2.05	0.75	-2.75	0.01	Support+ Inducement Social	1346.88	1493.73	1362	1422
socialsup_d1	-2.09	1.92	-1.09	0.28	Support+ Inducement Social	1346.88	1493.73	1362	1422
sex2	0.42	0.17	2.53	0.01	Support+ Inducement Social	1346.88	1493.73	1362	1422
age	0.02	0.01	2.59	0.01	Support+ Inducement Social	1346.88	1493.73	1362	1422
educ2	-0.76	0.43	-1.76	0.08	Support+ Inducement Social	1346.88	1493.73	1362	1422
educ3	-0.79	0.57	-1.40	0.16	Support+ Inducement Social	1346.88	1493.73	1362	1422
educ4	-0.26	0.37	-0.71	0.48	Support+ Inducement Social	1346.88	1493.73	1362	1422
educ5	-2.25	0.83	-2.71	0.01	Support+ Inducement Social	1346.88	1493.73	1362	1422
educ6	-0.51	0.40	-1.26	0.21	Support+ Inducement	1346.88	1493.73	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	0.78	0.44	1.78	0.08	Support+Inducement Social	1346.88	1493.73	1362	1422
empl3	-0.45	0.37	-1.21	0.22	Support+Inducement Social	1346.88	1493.73	1362	1422
empl4	-0.66	0.41	-1.62	0.11	Support+Inducement Social	1346.88	1493.73	1362	1422
empl5	-0.82	0.36	-2.25	0.02	Support+Inducement Social	1346.88	1493.73	1362	1422
empl6	-0.29	0.50	-0.58	0.56	Support+Inducement Social	1346.88	1493.73	1362	1422
empl7	-0.26	0.42	-0.62	0.53	Support+Inducement Social	1346.88	1493.73	1362	1422
empl8	0.14	0.60	0.24	0.81	Support+Inducement Social	1346.88	1493.73	1362	1422
empl9	-0.11	0.51	-0.22	0.82	Support+Inducement Social	1346.88	1493.73	1362	1422
empl10	-0.01	0.44	-0.03	0.98	Support+Inducement Social	1346.88	1493.73	1362	1422
empl11	1.31	0.49	2.69	0.01	Support+Inducement	1346.88	1493.73	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
marr_stat2	-0.33	0.47	-0.70	0.49	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
marr_stat3	0.05	0.33	0.16	0.87	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
marr_stat4	0.24	0.24	0.97	0.33	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
marr_stat5	-15.49	943.00	-0.02	0.99	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
marr_stat6	0.43	0.23	1.87	0.06	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
average_income	-0.00	0.00	-0.46	0.65	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
location_size2	-0.24	0.28	-0.85	0.40	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
location_size3	-0.49	0.31	-1.60	0.11	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
location_size4	-0.13	0.29	-0.44	0.66	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
location_size5	0.12	0.28	0.42	0.68	Support+Inducement	1346.88	1493.73	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.16	0.07	2.37	0.02	Social Support+ Inducement	1346.88	1493.73	1362	1422
elect_induc	0.31	0.28	1.10	0.27	Social Support+ Inducement	1346.88	1493.73	1362	1422
socialsup_d1:sex2	0.61	0.43	1.40	0.16	Social Support+ Inducement	1346.88	1493.73	1362	1422
socialsup_d1:age	0.01	0.02	0.36	0.72	Social Support+ Inducement	1346.88	1493.73	1362	1422
socialsup_d1:educ2	1.36	1.19	1.14	0.25	Social Support+ Inducement	1346.88	1493.73	1362	1422
socialsup_d1:educ3	0.18	1.44	0.12	0.90	Social Support+ Inducement	1346.88	1493.73	1362	1422
socialsup_d1:educ4	0.44	1.08	0.41	0.68	Social Support+ Inducement	1346.88	1493.73	1362	1422
socialsup_d1:educ5	-12.82	778.10	-0.02	0.99	Social Support+ Inducement	1346.88	1493.73	1362	1422
socialsup_d1:educ6	0.52	1.11	0.47	0.64	Social Support+ Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl2	-1.01	1.05	-0.96	0.34	Social Support+ Inducement	1346.88	1493.73	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
socialsup_d1:empl3	-0.08	0.83	-0.10	0.92	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl4	-0.21	0.92	-0.23	0.82	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl5	-0.10	0.80	-0.13	0.90	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl6	-15.07	606.19	-0.02	0.98	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl7	-0.26	0.93	-0.28	0.78	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl8	-1.03	1.46	-0.70	0.48	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl9	0.87	1.11	0.78	0.44	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl10	-0.36	1.03	-0.35	0.73	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:empl11	-3.11	1.39	-2.24	0.03	Support+Inducement	1346.88	1493.73	1362	1422
socialsup_d1:marr_stat2	0.84	0.94	0.89	0.37	Support+Inducement	1346.88	1493.73	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
socialsup_d1:marr_stat3	-0.46	0.87	-0.53	0.60	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:marr_stat4	-0.66	0.62	-1.07	0.29	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:marr_stat5	0.66	2595.85	0.00	1.00	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:marr_stat6	-0.71	0.58	-1.23	0.22	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:average_income	0.00	0.00	2.03	0.04	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:location_size2	0.55	0.68	0.81	0.42	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:location_size3	0.19	0.77	0.25	0.80	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:location_size4	0.71	0.72	0.99	0.32	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:location_size5	0.34	0.71	0.48	0.63	Support+Inducement	1346.88	1493.73	1362	1422
					Social				
socialsup_d1:famil_numb	0.13	0.14	0.94	0.35	Support+Inducement	1346.88	1493.73	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
socialsup_d1:elect_induc	-1.99	1.14	-1.75	0.08	Support+ Inducement Economic	1346.88	1493.73	1362	1422
(Intercept)	-2.60	0.84	-3.10	0.00	Development+ Inducement Economic	1330.67	1450.03	1362	1422
econdev_d1	-0.36	2.04	-0.18	0.86	Development+ Inducement Economic	1330.67	1450.03	1362	1422
sex2	0.61	0.18	3.28	0.00	Development+ Inducement Economic	1330.67	1450.03	1362	1422
age	0.01	0.01	1.36	0.17	Development+ Inducement Economic	1330.67	1450.03	1362	1422
educ2	0.10	0.43	0.24	0.81	Development+ Inducement Economic	1330.67	1450.03	1362	1422
educ3	0.12	0.54	0.22	0.83	Development+ Inducement Economic	1330.67	1450.03	1362	1422
educ4	-0.03	0.40	-0.08	0.93	Development+ Inducement Economic	1330.67	1450.03	1362	1422
educ5	0.49	0.89	0.55	0.58	Development+ Inducement Economic	1330.67	1450.03	1362	1422
educ6	-0.67	0.45	-1.50	0.13	Development+ Inducement	1330.67	1450.03	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	1.46	0.57	2.55	0.01	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl3	0.47	0.50	0.94	0.35	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl4	-0.03	0.53	-0.05	0.96	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl5	0.20	0.49	0.41	0.68	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl6	-0.69	0.76	-0.92	0.36	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl7	1.10	0.52	2.09	0.04	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl8	0.83	0.63	1.32	0.19	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl9	0.85	0.59	1.45	0.15	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl10	0.71	0.57	1.26	0.21	Economic Development+ Inducement	1330.67	1450.03	1362	1422
empl11	-0.05	0.69	-0.07	0.94	Economic Development+ Inducement	1330.67	1450.03	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	0.09	0.40	0.23	0.82	Economic Development+ Inducement	1330.67	1450.03	1362	1422
marr_stat3	-0.33	0.28	-1.18	0.24	Economic Development+ Inducement	1330.67	1450.03	1362	1422
marr_stat4	0.29	0.27	1.09	0.28	Economic Development+ Inducement	1330.67	1450.03	1362	1422
marr_stat5	-14.59	522.90	-0.03	0.98	Economic Development+ Inducement	1330.67	1450.03	1362	1422
marr_stat6	0.53	0.23	2.27	0.02	Economic Development+ Inducement	1330.67	1450.03	1362	1422
average_income	0.00	0.00	0.14	0.89	Economic Development+ Inducement	1330.67	1450.03	1362	1422
location_size2	-0.52	0.30	-1.71	0.09	Economic Development+ Inducement	1330.67	1450.03	1362	1422
location_size3	-0.75	0.30	-2.48	0.01	Economic Development+ Inducement	1330.67	1450.03	1362	1422
location_size4	-0.35	0.30	-1.16	0.24	Economic Development+ Inducement	1330.67	1450.03	1362	1422
location_size5	-0.51	0.31	-1.61	0.11	Economic Development+ Inducement	1330.67	1450.03	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.13	0.06	1.96	0.05	Economic Development+ Inducement	1330.67	1450.03	1362	1422
elect_induc	0.05	0.33	0.15	0.88	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:sex2	-0.43	0.43	-1.00	0.32	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:age	0.03	0.02	1.37	0.17	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:educ2	-1.18	0.93	-1.27	0.20	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:educ3	-1.73	1.25	-1.38	0.17	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:educ4	-0.71	0.84	-0.84	0.40	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:educ5	-15.01	704.29	-0.02	0.98	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:educ6	-0.53	0.95	-0.56	0.57	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl2	-0.93	1.38	-0.67	0.50	Economic Development+ Inducement	1330.67	1450.03	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:empl3	0.60	1.11	0.53	0.59	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl4	0.09	1.16	0.08	0.94	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl5	-0.94	1.12	-0.84	0.40	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl6	0.60	1.70	0.35	0.72	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl7	-0.91	1.19	-0.77	0.44	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl8	-1.06	1.49	-0.71	0.48	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl9	0.36	1.31	0.27	0.78	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl10	-0.54	1.35	-0.40	0.69	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:empl11	-0.99	1.62	-0.61	0.54	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:marr_stat2	0.28	0.89	0.31	0.75	Economic Development+ Inducement	1330.67	1450.03	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:marr_stat3	0.46	0.68	0.68	0.50	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:marr_stat4	-0.78	0.69	-1.13	0.26	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:marr_stat5	1.86	1174.05	0.00	1.00	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:marr_stat6	-0.03	0.59	-0.06	0.96	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:average_income	-0.00	0.00	-0.14	0.89	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:location_size2	0.54	0.75	0.71	0.48	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:location_size3	0.72	0.78	0.93	0.35	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:location_size4	0.46	0.74	0.62	0.53	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:location_size5	1.07	0.76	1.41	0.16	Economic Development+ Inducement	1330.67	1450.03	1362	1422
econdev_d1:famil_numb	0.01	0.17	0.08	0.94	Economic Development+ Inducement	1330.67	1450.03	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
econdev_d1:elect_induc	-1.10	0.77	-1.42	0.15	Economic Development+ Inducement Personal	1330.67	1450.03	1362	1422
(Intercept)	-8.63	4.21	-2.05	0.04	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1	6.21	4.29	1.45	0.15	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
sex2	-0.16	0.59	-0.27	0.79	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
age	0.04	0.03	1.18	0.24	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
educ2	3.03	3.38	0.89	0.37	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
educ3	0.03	3.96	0.01	0.99	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
educ4	1.91	3.32	0.57	0.57	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
educ5	-12.00	891.63	-0.01	0.99	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
educ6	2.34	3.35	0.70	0.49	Connections+ Inducement	1358.08	1488.62	1363	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	-0.37	1.45	-0.25	0.80	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl3	0.50	0.97	0.52	0.60	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl4	-0.80	1.26	-0.63	0.53	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl5	-2.25	1.27	-1.77	0.08	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl6	-4.51	3.50	-1.29	0.20	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl7	0.06	1.40	0.04	0.97	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl8	-15.09	633.53	-0.02	0.98	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl9	-1.25	3.31	-0.38	0.71	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl10	-0.18	1.75	-0.10	0.92	Personal Connections+ Inducement	1358.08	1488.62	1363	1422
empl11	-4.96	3.53	-1.41	0.16	Personal Connections+ Inducement	1358.08	1488.62	1363	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-0.81	1.27	-0.64	0.52	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
marr_stat3	1.50	1.01	1.48	0.14	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
marr_stat4	2.05	1.05	1.96	0.05	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
marr_stat5	-14.61	489.49	-0.03	0.98	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
marr_stat6	1.70	0.90	1.89	0.06	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
average_income	0.00	0.00	1.41	0.16	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
location_size2	0.27	0.97	0.28	0.78	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
location_size3	-0.41	1.06	-0.39	0.69	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
location_size4	0.33	0.97	0.34	0.74	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
location_size5	1.52	0.94	1.61	0.11	Connections+ Inducement	1358.08	1488.62	1363	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.84	0.28	3.03	0.00	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
elect_induc	-0.24	0.99	-0.24	0.81	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:sex2	0.78	0.61	1.28	0.20	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:age	-0.02	0.03	-0.63	0.53	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:educ2	-3.57	3.41	-1.05	0.30	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:educ3	-0.64	4.00	-0.16	0.87	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:educ4	-2.29	3.35	-0.69	0.49	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:educ5	11.70	891.63	0.01	0.99	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:educ6	-3.12	3.38	-0.92	0.36	Personal Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl2	1.09	1.53	0.71	0.48	Personal Connections+ Inducement	1358.08	1488.62	1363	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:empl3	-0.29	1.05	-0.28	0.78	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl4	0.66	1.34	0.49	0.62	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl5	2.13	1.34	1.59	0.11	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl6	3.36	3.59	0.94	0.35	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl7	0.36	1.47	0.25	0.81	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl8	15.66	633.53	0.02	0.98	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl9	1.81	3.35	0.54	0.59	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl10	0.49	1.83	0.27	0.79	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:empl11	4.69	3.62	1.30	0.19	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:marr_stat2	0.83	1.33	0.62	0.53	Connections+ Inducement	1358.08	1488.62	1363	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:marr_stat3	-1.81	1.05	-1.72	0.09	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:marr_stat4	-2.17	1.08	-2.01	0.04	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:marr_stat5					Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:marr_stat6	-1.58	0.93	-1.70	0.09	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:average_income	-0.00	0.00	-1.15	0.25	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:location_size2	-0.25	1.01	-0.25	0.80	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:location_size3	0.32	1.10	0.29	0.77	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:location_size4	-0.25	1.02	-0.25	0.80	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:location_size5	-1.43	0.99	-1.44	0.15	Connections+ Inducement Personal	1358.08	1488.62	1363	1422
personconnect_d1:famil_numb	-0.74	0.28	-2.61	0.01	Connections+ Inducement	1358.08	1488.62	1363	1422



term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl2	1.20	0.74	1.62	0.11	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl3	1.17	0.63	1.86	0.06	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl4	0.94	0.68	1.38	0.17	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl5	-0.18	0.66	-0.27	0.79	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl6	-14.33	597.41	-0.02	0.98	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl7	0.47	0.67	0.70	0.48	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl8	1.63	0.88	1.86	0.06	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl9	1.19	0.90	1.33	0.18	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl10	-0.53	0.89	-0.60	0.55	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
empl11	-1.00	1.58	-0.63	0.53	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
marr_stat2	-0.18	0.64	-0.28	0.78	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
marr_stat3	-0.16	0.41	-0.40	0.69	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
marr_stat4	-1.15	0.49	-2.35	0.02	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
marr_stat5	-14.64	1480.49	-0.01	0.99	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
marr_stat6	-0.06	0.39	-0.15	0.88	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
average_income	0.00	0.00	0.44	0.66	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
location_size2	-0.61	0.46	-1.33	0.18	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
location_size3	-0.71	0.48	-1.48	0.14	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
location_size4	-0.98	0.47	-2.07	0.04	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
location_size5	-0.34	0.47	-0.73	0.47	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
famil_numb	0.18	0.11	1.64	0.10	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
elect_induc	-1.37	0.69	-2.00	0.05	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:sex2	0.01	0.33	0.03	0.98	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:age	-0.02	0.02	-1.38	0.17	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:educ2	2.23	0.82	2.72	0.01	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:educ3	1.66	1.09	1.51	0.13	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:educ4	2.54	0.76	3.33	0.00	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:educ5	17.27	730.33	0.02	0.98	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:educ6	2.57	0.81	3.16	0.00	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl2	-0.49	0.90	-0.55	0.59	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:empl3	-0.97	0.76	-1.29	0.20	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl4	-1.22	0.84	-1.45	0.15	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl5	-0.16	0.80	-0.20	0.84	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl6	13.52	597.41	0.02	0.98	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl7	-0.16	0.83	-0.20	0.84	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl8	-1.54	1.09	-1.42	0.16	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl9	-1.06	1.06	-0.99	0.32	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl10	0.80	1.04	0.77	0.44	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:empl11	0.92	1.76	0.52	0.60	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:marr_stat2	0.30	0.77	0.39	0.69	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:marr_stat3	0.10	0.52	0.19	0.85	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:marr_stat4	1.71	0.57	3.00	0.00	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:marr_stat5	-0.47	1818.90	-0.00	1.00	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:marr_stat6	0.36	0.47	0.76	0.45	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:average_income	0.00	0.00	0.23	0.82	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:location_size2	0.72	0.59	1.23	0.22	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:location_size3	0.61	0.62	0.99	0.32	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:location_size4	1.13	0.61	1.86	0.06	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:location_size5	0.55	0.60	0.93	0.35	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422
indivwealth_d1:famil_numb	-0.07	0.13	-0.52	0.60	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:elect_induc	1.20	0.78	1.54	0.12	Individual Wealth+ Inducement	1353.88	1503.19	1362	1422

Table 12: GLM model: UR core voters vs other parties/non-voters + Inducement interaction

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
(Intercept)	-6.94	1.29	-5.36	0.00	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1	2.20	2.41	0.91	0.36	Infrastructural development + Inducement	864.18	1037.60	1256	1316
sex2	0.70	0.23	3.07	0.00	Infrastructural development + Inducement	864.18	1037.60	1256	1316
age	0.04	0.01	3.36	0.00	Infrastructural development + Inducement	864.18	1037.60	1256	1316
educ2	0.60	0.68	0.88	0.38	Infrastructural development + Inducement	864.18	1037.60	1256	1316
educ3	0.24	0.77	0.31	0.76	Infrastructural development + Inducement	864.18	1037.60	1256	1316
educ4	0.67	0.64	1.06	0.29	Infrastructural development + Inducement	864.18	1037.60	1256	1316
educ5	-0.09	1.05	-0.08	0.94	Infrastructural development + Inducement	864.18	1037.60	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	0.85	0.66	1.28	0.20	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl2	0.24	0.91	0.26	0.79	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl3	1.19	0.79	1.51	0.13	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl4	0.98	0.80	1.22	0.22	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl5	0.77	0.80	0.96	0.34	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl6	-14.52	1193.11	-0.01	0.99	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl7	1.44	0.81	1.78	0.08	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl8	1.64	0.89	1.85	0.06	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl9	1.46	0.90	1.64	0.10	Infrastructural development + Inducement	864.18	1037.60	1256	1316
empl10	0.71	1.03	0.69	0.49	Infrastructural development + Inducement	864.18	1037.60	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-0.35	1.88	-0.19	0.85	Infrastructural development + Inducement	864.18	1037.60	1256	1316
marr_stat2	-1.03	0.77	-1.33	0.18	Infrastructural development + Inducement	864.18	1037.60	1256	1316
marr_stat3	-0.49	0.32	-1.55	0.12	Infrastructural development + Inducement	864.18	1037.60	1256	1316
marr_stat4	-0.74	0.34	-2.17	0.03	Infrastructural development + Inducement	864.18	1037.60	1256	1316
marr_stat5	-17.12	2528.05	-0.01	0.99	Infrastructural development + Inducement	864.18	1037.60	1256	1316
marr_stat6	-0.30	0.35	-0.85	0.40	Infrastructural development + Inducement	864.18	1037.60	1256	1316
average_income	0.00	0.00	2.40	0.02	Infrastructural development + Inducement	864.18	1037.60	1256	1316
location_size2	1.59	0.43	3.74	0.00	Infrastructural development + Inducement	864.18	1037.60	1256	1316
location_size3	1.25	0.45	2.81	0.01	Infrastructural development + Inducement	864.18	1037.60	1256	1316
location_size4	1.01	0.45	2.27	0.02	Infrastructural development + Inducement	864.18	1037.60	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	1.47	0.44	3.33	0.00	Infrastructural development + Inducement	864.18	1037.60	1256	1316
famil_numb	-0.02	0.09	-0.16	0.87	Infrastructural development + Inducement	864.18	1037.60	1256	1316
elect_induc	-0.82	0.50	-1.63	0.10	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:sex2	0.64	0.50	1.27	0.20	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:age	-0.03	0.02	-1.13	0.26	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:educ2	-0.57	1.23	-0.46	0.65	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:educ3	-17.57	1596.24	-0.01	0.99	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:educ4	-1.23	1.17	-1.06	0.29	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:educ5	-16.36	1836.25	-0.01	0.99	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:educ6	-1.37	1.26	-1.09	0.28	Infrastructural development + Inducement	864.18	1037.60	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:empl2	-19.08	1539.89	-0.01	0.99	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl3	-2.42	1.16	-2.08	0.04	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl4	-2.35	1.25	-1.89	0.06	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl5	-1.38	1.17	-1.18	0.24	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl6	-3.21	2113.79	-0.00	1.00	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl7	-2.26	1.25	-1.80	0.07	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl8	0.05	1.42	0.03	0.97	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl9	-2.25	1.45	-1.55	0.12	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl10	-17.30	1664.53	-0.01	0.99	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:empl11	-16.39	3315.73	-0.00	1.00	Infrastructural development + Inducement	864.18	1037.60	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:marr_stat2	-0.73	1.45	-0.50	0.62	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:marr_stat3	0.27	0.73	0.36	0.72	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:marr_stat4	0.02	0.74	0.02	0.98	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:marr_stat5	-2.05	3850.58	-0.00	1.00	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:marr_stat6	-1.16	0.90	-1.29	0.20	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:average_income	0.00	0.00	2.62	0.01	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:location_size2	-0.65	0.98	-0.67	0.51	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:location_size3	-0.03	1.00	-0.03	0.98	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:location_size4	0.49	0.95	0.51	0.61	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:location_size5	0.04	0.96	0.04	0.97	Infrastructural development + Inducement	864.18	1037.60	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
infrastr_d1:famil_numb	0.26	0.22	1.19	0.23	Infrastructural development + Inducement	864.18	1037.60	1256	1316
infrastr_d1:elect_induc	0.78	1.20	0.65	0.52	Infrastructural development + Inducement	864.18	1037.60	1256	1316
(Intercept)	-3.70	0.90	-4.11	0.00	Social Support+ Inducement	898.16	1056.19	1256	1316
socialsup_d1	-17.70	1528.35	-0.01	0.99	Social Support+ Inducement	898.16	1056.19	1256	1316
sex2	0.66	0.19	3.39	0.00	Social Support+ Inducement	898.16	1056.19	1256	1316
age	0.02	0.01	2.35	0.02	Social Support+ Inducement	898.16	1056.19	1256	1316
educ2	0.29	0.51	0.56	0.57	Social Support+ Inducement	898.16	1056.19	1256	1316
educ3	0.08	0.59	0.14	0.89	Social Support+ Inducement	898.16	1056.19	1256	1316
educ4	-0.20	0.47	-0.42	0.67	Social Support+ Inducement	898.16	1056.19	1256	1316
educ5	-0.92	0.89	-1.03	0.30	Social Support+ Inducement	898.16	1056.19	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	0.38	0.48	0.79	0.43	Social Support+ Inducement	898.16	1056.19	1256	1316
empl2	-0.60	0.58	-1.04	0.30	Social Support+ Inducement	898.16	1056.19	1256	1316
empl3	-0.49	0.41	-1.19	0.23	Social Support+ Inducement	898.16	1056.19	1256	1316
empl4	-0.65	0.46	-1.40	0.16	Social Support+ Inducement	898.16	1056.19	1256	1316
empl5	-0.55	0.40	-1.36	0.17	Social Support+ Inducement	898.16	1056.19	1256	1316
empl6	-16.79	904.06	-0.02	0.99	Social Support+ Inducement	898.16	1056.19	1256	1316
empl7	-0.09	0.47	-0.19	0.85	Social Support+ Inducement	898.16	1056.19	1256	1316
empl8	1.31	0.55	2.38	0.02	Social Support+ Inducement	898.16	1056.19	1256	1316
empl9	-1.07	0.65	-1.63	0.10	Social Support+ Inducement	898.16	1056.19	1256	1316
empl10	-0.84	0.56	-1.48	0.14	Social Support+ Inducement	898.16	1056.19	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-1.85	1.23	-1.51	0.13	Support+ Inducement Social	898.16	1056.19	1256	1316
marr_stat2	-1.17	0.65	-1.79	0.07	Support+ Inducement Social	898.16	1056.19	1256	1316
marr_stat3	-0.62	0.39	-1.60	0.11	Support+ Inducement Social	898.16	1056.19	1256	1316
marr_stat4	-0.24	0.28	-0.86	0.39	Support+ Inducement Social	898.16	1056.19	1256	1316
marr_stat5	-17.99	2394.28	-0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
marr_stat6	-0.54	0.30	-1.78	0.08	Support+ Inducement Social	898.16	1056.19	1256	1316
average_income	0.00	0.00	1.14	0.25	Support+ Inducement Social	898.16	1056.19	1256	1316
location_size2	0.53	0.38	1.39	0.16	Support+ Inducement Social	898.16	1056.19	1256	1316
location_size3	1.25	0.37	3.34	0.00	Support+ Inducement Social	898.16	1056.19	1256	1316
location_size4	0.97	0.38	2.52	0.01	Support+ Inducement	898.16	1056.19	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	1.19	0.38	3.14	0.00	Support+ Inducement Social	898.16	1056.19	1256	1316
famil_numb	0.05	0.08	0.62	0.53	Support+ Inducement Social	898.16	1056.19	1256	1316
elect_induc	0.54	0.28	1.92	0.05	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:sex2	0.59	0.64	0.92	0.36	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:age	0.01	0.03	0.51	0.61	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:educ2	-0.52	1.40	-0.37	0.71	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:educ3	-0.44	1.72	-0.26	0.80	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:educ4	-0.89	1.16	-0.77	0.44	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:educ5	-15.36	2047.43	-0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:educ6	-0.46	1.21	-0.38	0.70	Support+ Inducement	898.16	1056.19	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:empl2	0.21	2190.04	0.00	1.00	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl3	16.96	1528.35	0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl4	16.65	1528.35	0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl5	16.37	1528.35	0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl6	18.87	2341.85	0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl7	16.26	1528.35	0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl8	-1.37	2527.63	-0.00	1.00	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl9	17.14	1528.35	0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl10	16.60	1528.35	0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:empl11	1.28	2520.46	0.00	1.00	Support+ Inducement	898.16	1056.19	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
socialsup_d1:marr_stat2	-14.33	1607.31	-0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:marr_stat3	0.22	0.92	0.23	0.81	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:marr_stat4	0.02	0.81	0.03	0.98	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:marr_stat5	1.32	6642.91	0.00	1.00	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:marr_stat6	-1.06	1.23	-0.86	0.39	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:average_income	0.00	0.00	0.91	0.36	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:location_size2	0.42	0.96	0.44	0.66	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:location_size3	-0.91	1.06	-0.86	0.39	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:location_size4	-0.02	1.05	-0.01	0.99	Support+ Inducement Social	898.16	1056.19	1256	1316
socialsup_d1:location_size5	0.10	1.01	0.09	0.92	Support+ Inducement	898.16	1056.19	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
					Social				
socialsup_d1:famil_numb	0.11	0.17	0.63	0.53	Support+ Inducement	898.16	1056.19	1256	1316
socialsup_d1:elect_induc	-15.93	1126.62	-0.01	0.99	Support+ Inducement Social Economic	898.16	1056.19	1256	1316
(Intercept)	-29.73	12045.19	-0.00	1.00	Development+ Inducement Economic	942.20	1107.96	1257	1316
personconnect_d1	24.21	12045.19	0.00	1.00	Development+ Inducement Economic	942.20	1107.96	1257	1316
sex2	3.36	21.25	0.16	0.87	Development+ Inducement Economic	942.20	1107.96	1257	1316
age	0.06	0.83	0.08	0.94	Development+ Inducement Economic	942.20	1107.96	1257	1316
educ2	-18.08	10493.05	-0.00	1.00	Development+ Inducement Economic	942.20	1107.96	1257	1316
educ3	-4.39	34.85	-0.13	0.90	Development+ Inducement Economic	942.20	1107.96	1257	1316
educ4	-3.81	30.89	-0.12	0.90	Development+ Inducement Economic	942.20	1107.96	1257	1316
educ5	-22.94	32803.63	-0.00	1.00	Development+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	-3.06	30.08	-0.10	0.92	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl2	-20.99	16181.86	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl3	1.35	32.16	0.04	0.97	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl4	3.80	47.18	0.08	0.94	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl5	1.44	34.84	0.04	0.97	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl6	3.48	20304.63	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl7	-0.91	36.83	-0.02	0.98	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl8	-13.45	19215.99	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl9	4.26	37.71	0.11	0.91	Economic Development+ Inducement	942.20	1107.96	1257	1316
empl10	2.15	42.02	0.05	0.96	Economic Development+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-12.91	20215.43	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
marr_stat2	-19.70	17944.82	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
marr_stat3	0.92	21.16	0.04	0.97	Economic Development+ Inducement	942.20	1107.96	1257	1316
marr_stat4	-0.75	23.47	-0.03	0.97	Economic Development+ Inducement	942.20	1107.96	1257	1316
marr_stat5	-17.40	18939.12	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
marr_stat6	-19.67	9361.04	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
average_income	0.00	0.00	0.24	0.81	Economic Development+ Inducement	942.20	1107.96	1257	1316
location_size2	21.24	12044.90	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
location_size3	20.11	12044.94	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
location_size4	20.28	12044.89	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	16.21	12044.85	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
famil_numb	0.08	8.37	0.01	0.99	Economic Development+ Inducement	942.20	1107.96	1257	1316
elect_induc	-1.27	30.82	-0.04	0.97	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:sex2	-2.66	21.32	-0.12	0.90	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:age	-0.03	0.83	-0.04	0.97	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:educ2	18.31	10493.05	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:educ3	4.39	35.35	0.12	0.90	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:educ4	3.86	31.20	0.12	0.90	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:educ5	23.35	32803.63	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:educ6	3.29	30.43	0.11	0.91	Economic Development+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:empl2	20.85	16181.86	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl3	-0.91	32.47	-0.03	0.98	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl4	-3.63	47.44	-0.08	0.94	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl5	-1.21	35.15	-0.03	0.97	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl6	-19.22	22015.28	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl7	1.53	37.14	0.04	0.97	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl8	14.54	19215.99	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl9	-3.93	38.18	-0.10	0.92	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl10	-2.05	42.44	-0.05	0.96	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:empl11	11.85	20215.43	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:marr_stat2	18.75	17944.82	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:marr_stat3	-1.20	21.31	-0.06	0.96	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:marr_stat4	0.54	23.62	0.02	0.98	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:marr_stat5					Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:marr_stat6	19.36	9361.04	0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:average_income	-0.00	0.00	-0.22	0.82	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:location_size2	-20.44	12044.90	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:location_size3	-19.14	12044.94	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:location_size4	-19.06	12044.89	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316
personconnect_d1:location_size5	-14.97	12044.85	-0.00	1.00	Economic Development+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:famil_numb	0.07	8.39	0.01	0.99	Economic Development+ Inducement	942.20	1107.96	1257	1316
elect_induc:personconnect	0.14	5.42	0.03	0.98	Economic Development+ Inducement	942.20	1107.96	1257	1316
(Intercept)	-29.73	12045.19	-0.00	1.00	Personal Connections+ Inducement	942.20	1107.96	1257	1316
personconnect_d1	24.21	12045.19	0.00	1.00	Personal Connections+ Inducement	942.20	1107.96	1257	1316
sex2	3.36	21.25	0.16	0.87	Personal Connections+ Inducement	942.20	1107.96	1257	1316
age	0.06	0.83	0.08	0.94	Personal Connections+ Inducement	942.20	1107.96	1257	1316
educ2	-18.08	10493.05	-0.00	1.00	Personal Connections+ Inducement	942.20	1107.96	1257	1316
educ3	-4.39	34.85	-0.13	0.90	Personal Connections+ Inducement	942.20	1107.96	1257	1316
educ4	-3.81	30.89	-0.12	0.90	Personal Connections+ Inducement	942.20	1107.96	1257	1316
educ5	-22.94	32803.63	-0.00	1.00	Personal Connections+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	-3.06	30.08	-0.10	0.92	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl2	-20.99	16181.86	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl3	1.35	32.16	0.04	0.97	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl4	3.80	47.18	0.08	0.94	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl5	1.44	34.84	0.04	0.97	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl6	3.48	20304.63	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl7	-0.91	36.83	-0.02	0.98	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl8	-13.45	19215.99	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl9	4.26	37.71	0.11	0.91	Connections+ Inducement Personal	942.20	1107.96	1257	1316
empl10	2.15	42.02	0.05	0.96	Connections+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-12.91	20215.43	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
marr_stat2	-19.70	17944.82	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
marr_stat3	0.92	21.16	0.04	0.97	Connections+ Inducement Personal	942.20	1107.96	1257	1316
marr_stat4	-0.75	23.47	-0.03	0.97	Connections+ Inducement Personal	942.20	1107.96	1257	1316
marr_stat5	-17.40	18939.12	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
marr_stat6	-19.67	9361.04	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
average_income	0.00	0.00	0.24	0.81	Connections+ Inducement Personal	942.20	1107.96	1257	1316
location_size2	21.24	12044.90	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
location_size3	20.11	12044.94	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
location_size4	20.28	12044.89	0.00	1.00	Connections+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	16.21	12044.85	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
famil_numb	0.08	8.37	0.01	0.99	Connections+ Inducement Personal	942.20	1107.96	1257	1316
elect_induc	-1.27	30.82	-0.04	0.97	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:sex2	-2.66	21.32	-0.12	0.90	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:age	-0.03	0.83	-0.04	0.97	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:educ2	18.31	10493.05	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:educ3	4.39	35.35	0.12	0.90	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:educ4	3.86	31.20	0.12	0.90	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:educ5	23.35	32803.63	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:educ6	3.29	30.43	0.11	0.91	Connections+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:empl2	20.85	16181.86	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl3	-0.91	32.47	-0.03	0.98	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl4	-3.63	47.44	-0.08	0.94	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl5	-1.21	35.15	-0.03	0.97	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl6	-19.22	22015.28	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl7	1.53	37.14	0.04	0.97	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl8	14.54	19215.99	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl9	-3.93	38.18	-0.10	0.92	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl10	-2.05	42.44	-0.05	0.96	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:empl11	11.85	20215.43	0.00	1.00	Connections+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:marr_stat2	18.75	17944.82	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:marr_stat3	-1.20	21.31	-0.06	0.96	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:marr_stat4	0.54	23.62	0.02	0.98	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:marr_stat5					Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:marr_stat6	19.36	9361.04	0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:average_income	-0.00	0.00	-0.22	0.82	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:location_size2	-20.44	12044.90	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:location_size3	-19.14	12044.94	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:location_size4	-19.06	12044.89	-0.00	1.00	Connections+ Inducement Personal	942.20	1107.96	1257	1316
personconnect_d1:location_size5	-14.97	12044.85	-0.00	1.00	Connections+ Inducement	942.20	1107.96	1257	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
personconnect_d1:famil_numb	0.07	8.39	0.01	0.99	Personal Connections+ Inducement Personal	942.20	1107.96	1257	1316
elect_induc:personconnect	0.14	5.42	0.03	0.98	Connections+ Inducement Individual	942.20	1107.96	1257	1316
(Intercept)	-5.56	2.00	-2.79	0.01	Wealth+ Inducement Individual	916.61	1090.93	1256	1316
indivwealth_d1	-0.06	2.28	-0.03	0.98	Wealth+ Inducement Individual	916.61	1090.93	1256	1316
sex2	1.90	0.46	4.13	0.00	Wealth+ Inducement Individual	916.61	1090.93	1256	1316
age	0.05	0.02	2.38	0.02	Wealth+ Inducement Individual	916.61	1090.93	1256	1316
educ2	-1.32	0.77	-1.70	0.09	Wealth+ Inducement Individual	916.61	1090.93	1256	1316
educ3	-1.42	1.07	-1.33	0.18	Wealth+ Inducement Individual	916.61	1090.93	1256	1316
educ4	-2.03	0.77	-2.64	0.01	Wealth+ Inducement Individual	916.61	1090.93	1256	1316
educ5	-16.21	1066.34	-0.02	0.99	Wealth+ Inducement	916.61	1090.93	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
educ6	-1.88	0.86	-2.19	0.03	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl2	-15.14	861.96	-0.02	0.99	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl3	1.22	1.10	1.11	0.27	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl4	0.49	1.24	0.39	0.69	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl5	0.72	1.12	0.65	0.52	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl6	-13.80	924.81	-0.01	0.99	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl7	0.40	1.12	0.36	0.72	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl8	2.59	1.30	1.99	0.05	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl9	0.93	1.44	0.65	0.52	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
empl10	-2.17	2.91	-0.75	0.46	Individual Wealth+ Inducement	916.61	1090.93	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
empl11	-14.40	1232.45	-0.01	0.99	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
marr_stat2	-1.58	1.43	-1.10	0.27	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
marr_stat3	0.09	0.56	0.15	0.88	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
marr_stat4	-0.87	0.59	-1.48	0.14	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
marr_stat5	-15.67	2229.19	-0.01	0.99	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
marr_stat6	-0.62	0.73	-0.85	0.40	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
average_income	0.00	0.00	2.48	0.01	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
location_size2	0.11	0.81	0.13	0.89	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
location_size3	0.51	0.81	0.63	0.53	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
location_size4	-0.41	0.81	-0.50	0.61	Individual Wealth+ Inducement	916.61	1090.93	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
location_size5	0.90	0.78	1.15	0.25	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
famil_numb	0.18	0.14	1.34	0.18	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
elect_induc	-2.20	1.41	-1.56	0.12	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:sex2	-1.47	0.51	-2.91	0.00	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:age	-0.02	0.02	-0.85	0.39	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:educ2	1.72	0.97	1.78	0.08	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:educ3	2.14	1.27	1.69	0.09	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:educ4	2.45	0.94	2.61	0.01	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:educ5	16.72	1066.34	0.02	0.99	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:educ6	2.57	1.02	2.51	0.01	Individual Wealth+ Inducement	916.61	1090.93	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:empl2	15.51	861.96	0.02	0.99	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl3	-0.65	1.22	-0.53	0.60	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl4	0.03	1.37	0.02	0.98	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl5	-0.35	1.25	-0.28	0.78	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl6	-0.41	1102.78	-0.00	1.00	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl7	0.35	1.26	0.28	0.78	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl8	-1.46	1.47	-0.99	0.32	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl9	-0.19	1.58	-0.12	0.91	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl10	2.85	2.99	0.96	0.34	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:empl11	13.81	1232.45	0.01	0.99	Individual Wealth+ Inducement	916.61	1090.93	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:marr_stat2	0.53	1.61	0.33	0.74	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:marr_stat3	-0.33	0.64	-0.52	0.61	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:marr_stat4	0.88	0.67	1.31	0.19	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:marr_stat5	-0.97	2796.79	-0.00	1.00	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:marr_stat6	0.09	0.80	0.11	0.91	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:average_income	-0.00	0.00	-1.17	0.24	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:location_size2	0.95	0.96	0.99	0.32	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:location_size3	0.53	0.96	0.55	0.58	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:location_size4	1.86	0.96	1.93	0.05	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:location_size5	0.27	0.94	0.29	0.78	Individual Wealth+ Inducement	916.61	1090.93	1256	1316

term	estimate	std.error	statistic	p.value	model_name	Deviance	NullDeviance	DF	n
indivwealth_d1:famil_numb	-0.12	0.16	-0.74	0.46	Individual Wealth+ Inducement	916.61	1090.93	1256	1316
indivwealth_d1:elect_induc	2.07	1.47	1.41	0.16	Individual Wealth+ Inducement	916.61	1090.93	1256	1316

Table 13: Average Marginal Contrasts: UR core and swing voters by Inducement levels (1, 0)

term	contrast	estimate	p.value	s.value	conf_low	conf_high	predicted_lo	predicted_hi	pred	model	induc
Infrastructural development (1)	ln(odds(1) odds(0))	2.01	0.29	1.80	0.56	7.24	0.33	0.52	0.33	UR voters vs other parties + inducement	0.00
Infrastructural development (1)	ln(odds(1) odds(0))	0.90	0.53	0.92	0.66	1.24	0.47	0.44	0.47	UR voters vs other parties + inducement	1.00
Social support (1)	ln(odds(1) odds(0))	0.07	0.12	3.10	0.00	1.97	0.57	0.05	0.05	UR voters vs other parties + inducement	0.00
Social support (1)	ln(odds(1) odds(0))	0.70	0.05	4.20	0.49	1.01	0.48	0.41	0.41	UR voters vs other parties + inducement	1.00
Economic development (1)	ln(odds(1) odds(0))	0.29	0.09	3.52	0.07	1.20	0.52	0.18	0.52	UR voters vs other parties + inducement	0.00
Economic development (1)	ln(odds(1) odds(0))	1.24	0.21	2.28	0.89	1.72	0.43	0.53	0.43	UR voters vs other parties + inducement	1.00
Personal connections (1)	ln(odds(1) odds(0))	2.94	0.40	1.32	0.24	36.08	0.07	0.39	0.39	UR voters vs other parties + inducement	0.00
Personal connections (1)	ln(odds(1) odds(0))	1.58	0.02	5.54	1.07	2.34	0.32	0.49	0.49	UR voters vs other parties + inducement	1.00
Individual wealth (1)	ln(odds(1) odds(0))	2.42	0.11	3.25	0.83	7.04	0.19	0.42	0.19	UR voters vs other parties + inducement	0.00
Individual wealth (1)	ln(odds(1) odds(0))	0.98	0.89	0.16	0.72	1.32	0.49	0.46	0.49	UR voters vs other parties + inducement	1.00

term	contrast	estimate	p.value	s.value	conf low	conf high	predicted lo	predicted hi	pred	model	induc
Infrastructural development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.51	0.49	1.03	0.47	4.93	0.49	0.56	0.49	UR voters vs non voting + inducement	0.00
Infrastructural development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.03	0.82	0.29	0.78	1.36	0.57	0.52	0.57	UR voters vs non voting + inducement	1.00
Social support (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.08	0.02	5.72	0.01	0.66	0.48	0.07	0.07	UR voters vs non voting + inducement	0.00
Social support (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.75	0.06	4.17	0.55	1.01	0.34	0.35	0.35	UR voters vs non voting + inducement	1.00
Economic development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.29	0.03	4.98	0.09	0.90	0.27	0.12	0.27	UR voters vs non voting + inducement	0.00
Economic development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.05	0.74	0.44	0.79	1.41	0.23	0.34	0.23	UR voters vs non voting + inducement	1.00
Personal connections (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.39	0.64	0.64	0.35	5.58	0.16	0.29	0.29	UR voters vs non voting + inducement	0.00
Personal connections (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.20	0.36	1.47	0.81	1.79	0.24	0.35	0.35	UR voters vs non voting + inducement	1.00
Individual wealth (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	3.26	0.01	6.43	1.30	8.17	0.14	0.29	0.14	UR voters vs non voting + inducement	0.00
Individual wealth (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	1.00	0.99	0.01	0.79	1.27	0.44	0.31	0.44	UR voters vs non voting + inducement	1.00

Table 14: Average Marginal Contrasts: UR core and swing voters by Inducement levels (1, 0)

term	contrast	estimate	p.value	s.value	conf low	conf high	predicted lo	predicted hi	pred	model	induc
Infrastructural development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.20	0.43	1.22	0.01	9.16	0.28	0.08	0.28	UR core vs swing voters+inducement	0.00
Infrastructural development (1)	$\ln(\text{odds}(1) / \text{odds}(0))$	0.60	0.01	6.22	0.37	0.89	0.44	0.38	0.44	UR core vs swing voters+inducement	1.00

term	contrast	estimate	p.value	s.value	conf low	conf high	predicted lo	predicted hi	pred	model	induc
Social support (1)	ln(odds(1) odds(0))	0.00	0.00	28.79	0.00	0.00	0.50	0.00	0.50	UR core vs swing voters+inducement	0.00
Social support (1)	ln(odds(1) odds(0))	0.70	0.12	3.07	0.40	1.11	0.54	0.34	0.54	UR core vs swing voters+inducement	1.00
Economic development (1)	ln(odds(1) odds(0))	0.30	0.34	1.56	0.03	3.45	0.71	0.00	0.71	UR core vs swing voters+inducement	0.00
Economic development (1)	ln(odds(1) odds(0))	1.00	0.87	0.21	0.65	1.65	0.64	0.02	0.64	UR core vs swing voters+inducement	1.00
Personal connections (1)	ln(odds(1) odds(0))	3.00	0.84	0.26	0.00		0.00	0.39	0.39	UR core vs swing voters+inducement	0.00
Personal connections (1)	ln(odds(1) odds(0))	1.30					0.00	0.49	0.49	UR core vs swing voters+inducement	1.00
Individual wealth (1)	ln(odds(1) odds(0))	7.10	0.03	5.21	1.25	40.60	0.01	0.55	0.55	UR core vs swing voters+inducement	0.00
Individual wealth (1)	ln(odds(1) odds(0))	1.80	0.00	8.67	1.24	2.69	0.06	0.54	0.54	UR core vs swing voters+inducement	1.00
Infrastructural development (1)	ln(odds(1) odds(0))	2.10	0.18	2.45	0.70	6.58	0.20	0.27	0.20	UR swing vs none other + inducement	0.00
Infrastructural development (1)	ln(odds(1) odds(0))	1.20	0.22	2.16	0.89	1.65	0.23	0.19	0.23	UR swing vs none other + inducement	1.00
Social support (1)	ln(odds(1) odds(0))	0.10	0.07	3.86	0.02	1.17	0.19	0.05	0.05	UR swing vs none other + inducement	0.00
Social support (1)	ln(odds(1) odds(0))	0.80	0.28	1.82	0.58	1.17	0.15	0.20	0.20	UR swing vs none other + inducement	1.00
Economic development (1)	ln(odds(1) odds(0))	0.40	0.23	2.13	0.10	1.71	0.12	0.10	0.12	UR swing vs none other + inducement	0.00
Economic development (1)	ln(odds(1) odds(0))	1.10	0.51	0.97	0.79	1.61	0.11	0.25	0.11	UR swing vs none other + inducement	1.00
Personal connections (1)	ln(odds(1) odds(0))	0.90	0.90	0.16	0.24	3.50	0.21	0.17	0.17	UR swing vs none other + inducement	0.00

term	contrast	estimate	p.value	s.value	conf low	conf high	predicted lo	predicted hi	pred	model	induc
Personal connections (1)	ln(odds(1) odds(0))	0.90	0.64	0.64	0.59	1.39	0.25	0.20	0.20	UR swing vs none other + inducement	1.00
Individual wealth (1)	ln(odds(1) odds(0))	2.20	0.16	2.68	0.74	6.36	0.10	0.15	0.10	UR swing vs none other + inducement	0.00
Individual wealth (1)	ln(odds(1) odds(0))	0.80	0.11	3.14	0.59	1.06	0.29	0.18	0.29	UR swing vs none other + inducement	1.00
Infrastructural development (1)	ln(odds(1) odds(0))	1.40	0.71	0.50	0.22	9.08	0.10	0.21	0.10	UR core vs none other + inducement	0.00
Infrastructural development (1)	ln(odds(1) odds(0))	0.70	0.06	4.04	0.49	1.02	0.20	0.22	0.20	UR core vs none other + inducement	1.00
Social support (1)	ln(odds(1) odds(0))	0.00	0.00	330.12	0.00	0.00	0.44	0.00	0.00	UR core vs none other + inducement	0.00
Social support (1)	ln(odds(1) odds(0))	0.70	0.07	3.79	0.41	1.04	0.31	0.25	0.25	UR core vs none other + inducement	1.00
Economic development (1)	ln(odds(1) odds(0))	0.10	0.05	4.41	0.02	0.98	0.27	0.03	0.27	UR core vs none other + inducement	0.00
Economic development (1)	ln(odds(1) odds(0))	1.00	0.93	0.10	0.68	1.52	0.16	0.16	0.16	UR core vs none other + inducement	1.00
Personal connections (1)	ln(odds(1) odds(0))	1.90	0.27	1.89	0.61	5.96	0.12	0.17	0.17	UR core vs none other + inducement	0.00
Personal connections (1)	ln(odds(1) odds(0))	2.40	0.05	4.44	1.02	5.87	0.16	0.23	0.23	UR core vs none other + inducement	1.00
Individual wealth (1)	ln(odds(1) odds(0))	7.10	0.03	4.87	1.16	44.04	0.05	0.18	0.05	UR core vs none other + inducement	0.00
Individual wealth (1)	ln(odds(1) odds(0))	1.30	0.12	3.03	0.93	1.89	0.31	0.20	0.31	UR core vs none other + inducement	1.00

# The big brothers: measuring influence of large firms on electoral mobilization in Russia

## Abstract

This paper delves into the engagement of big local business entities in the mobilization efforts during the Russian presidential and parliamentary elections spanning from 2012 to 2021. The research anticipates that the constraints imposed by the authoritarian regime result in suboptimal outcomes for clientelistic exchange, but these limitations are partly overcome by more stringent monitoring regime coupled with increased worker dependence on their workplace. Using comprehensive data covering all economic entities in Russia, the study shows that a smaller geographical distance between a large economic entity and the local electoral committee not only increases voter turnout but also contributes to protest voting in larger localities, while in smaller localities electoral mobilization achieves its goal and benefits the vote share of the dominant party and the incumbent.

## 1 Introduction

To what extent does electoral mobilization in authoritarian regimes result in favorable electoral outcomes for the incumbent and the dominant party? The electoral process and the manipulation of elections in authoritarian regimes are phenomena that go hand in hand and have a major impact on the broader political landscape of such regimes. While the regime wants to improve its access to information, increase its legitimacy, co-opt potential opposition and use democratic window dressing for the international community (Gandhi and Lust-Okar 2009; Magaloni 2006), it also cannot rely on free elections, which could endanger the very core of the regime - power concentrated in the hands of ruling elite. There are many different ways in which authoritarian regimes ensure that they win elections, including patronage, various clientelistic practices, and direct electoral fraud. However, it is important to note that electoral fraud doesn't always guarantee the dominant party or the incumbent the best electoral results, as pointed out by Rundlett and Svolik (2016). Moreover, patronage's effectiveness is constrained by the limited number of employment opportunities it can offer. Therefore, clientelism can play a significant role in achieving the desired electoral outcome.

When it comes to clientelistic practices, one of the most important components of successful clientelistic exchange is reliable brokers (Aspinall 2014; Stokes, Dunning and Nazareno 2013). Brokers ensure that the party can reach out not only to its core supporters but also to the swing voters who are crucial to the party's or politician's victory. But where do these reliable brokers they come from?

It is not uncommon for autocrats to establish close ties between the state and its economic actors in order to achieve political goals, but the nature of these relationships may vary. For example, according to Kamrava (2017), in Qatar the business community has close family ties with state politicians, blurring the line between state and business. These relationships are part of a complex network of power and influence, but unlike some others, they are primarily based on family and clan ties. Conversely, as shown by Gonzales and Prem (2018), in Chile during the Pinochet dictatorship, the military and civilian collaborators entered the business elite and controlled the largest and most important companies in the country. This relationship was not based on family ties, but rather as intervention of politically connected individuals through appointments to the governing boards of large corporations.

While there are studies on how various aspects of economic activity can be used for political gain by dictatorships, fewer show systematic involvement of business in political processes such as elections. At the same time, the use of companies and their employees to channel political support in favor of the ruling party is a well-established tradition for many states and historical periods (see Baland and Robinson 2006; Frye, Reuter and Szakonyi 2014; Kim and Gandhi 2010, Medina and Stokes 2007). As shown in Frye, Reuter, and Szakonyi 2014, not only the presence of business itself but rather the characteristics of the firms are determinant of the probability that the voters will be mobilized for the elections. For example, according to their findings, larger firms are more likely to have mobilized workers (2014, 213).

Why do authoritarian leaders choose to rely on private firms to secure political support rather than using other methods, such as repressive institutions or patronage mechanisms within the state apparatus? As described by Karcher and Schneider (2013), corporate involvement in politics can take the form of financial support to politicians and parties, institutionalized influence on policymaking or lobbying, as well as the use of structural power (e.g., the ability to move capital). Building on the argument about structural power, this research argues that private firms often possess the administrative capabilities to perform tasks such as electoral mobilization or other functions required by an authoritarian state. The authoritarian state itself, on the other hand, may lack such capabilities and may acquire them from accessible social structures.

At the same time, there is an ongoing discussion about the motives and constraints for business to cooperate with the government under dictatorship. The nature of these relationships further defines the potential nature of involvement in electoral mobilization, as well as its effectiveness. While some researchers see business organizations in authoritarian contexts as profit-seeking and therefore interested by default in cooperating with the state to achieve private gains (Gonzalo 2013, Pedreira-Campos 2021), others see them more as actors that depend on and conform to the rules of the game, rather than as protagonists (Lewes 2012, Wang and Jap2017). The latter approach also assumes that the political leadership defines the conditions under which the business community operates, which gives politicians leeway to extract all kinds of benefits from business actors when needed (Guriev and Sonin 2008). Rather than being mutually beneficial, this exchange is more like a toxic relationship where one party has more power to manipulate the other.

Thus, the clarity and intensity of business actors' motives in supporting the electoral mobilization of ruling elites in autocracy is ambiguous. In principle, private firms want to comply with the rules set by the autocrat, but their ability to do so is limited by their internal

monitoring capabilities. Furthermore, their willingness to exert extra efforts in support of specific candidates or political parties within the workplace may be influenced by a range of factors, including the characteristics of the economic entity, the structure of management, and external factors such as the presence and efficacy of electoral monitoring.

The purpose of this study is to further investigate the impact of business actors on electoral mobilisation in Russia. To this end, the information on all business entities operating in Russia was collected, and the actual physical distance between the larger businesses in a given area and the closest local electoral stations was calculated. Controlling for sectoral and regional variation, we find evidence that large firms located near the local electoral station positively affect voter turnout in the 2016 and 2021 Duma elections, as well as the 2012 and 2018 presidential elections. At the same time, under secret ballot conditions, inducement of voters can increase voter turnout, but it's difficult to establish direct control over the actual votes cast. Consequently, the results tend to reflect protest voting rather than support for the dominant party, which possesses administrative resources for mobilizing voters at workplaces. At the same time, the size of population assigned to electoral committee plays crucial role in provision of the dominant party and president with higher vote share.

## 2 Brokers and electoral mobilization

The process of business participation in electoral mobilization in authoritarian settings could be defined as part of clientelistic exchange, but with some limitations. The classic definition of clientelism implies "the exchange of citizens' votes in return for direct payments or continued access to employment, goods and services" (Kitschelt and Wilkinson 2007, 2). However, in regimes such as dominant party electoral authoritarianism, access to the resources that parties can use for clientelistic exchange is quite unequal (Weiss 2020). Moreover, while clientelism implies an imbalance in power relations in any regime type, authoritarian conditions differ in the severity of the costs associated with not participating in clientelistic exchange (Trantidis 2015).

A key actor in clientelistic exchange is the broker, usually a party member or supporter, who could be a public sector employees (such as teachers in Larreguy, Montiel Olea and Querubin 2017), religious leaders and community elders (Aspinall and Berenschot 2020), members of interest organizations (Holland and Palmer-Rubin 2015), or employers (Mares and Young 2019). Brokers acts as an intermediary between politicians (party leaders) and target voters, mostly at the local level (Stokes, Dunning and Nazareno 2013). Their distinction from party leaders lies primarily in their personalized interactions with voters, which plays a pivotal role in electoral mobilization.

However, the politician-broker-voter relationship has a problem of credible commitment at each level. How can the broker ensure that the client (voter) has fulfilled his part of the bargain and voted accordingly? How can a politician or a political party ensure that the broker distributes resources to voters and is committed to the party's victory?

Clientelistic exchange can involve several different electoral goals, including buying votes, turnout, or abstention (Cox and Kousser 1981, Stokes 2005, Nichter 2008). One of the key determinants of the choice of clientelistic exchange is the presence of a secret ballot and the ability of brokers to compromise secrecy and monitor votes (Nichter 2008, 20). As shown by

Stokes (2005), there are several ways to compromise ballot secrecy that increase monitoring of election outcomes and thus partly solve the principal-agent dilemma between brokers and voters. On the contrary, as per Nicther's research, motivating voters to participate in elections (such as through turnout buying) could also function as an inducement to support the incentivizing party, even without the need for additional voting monitoring (22-26).

At the same time, voters have to decide whether voting for the candidate or party involved in clientelism is their choice of preference. According to Stokes (2005) and Trantidis (2015), this is defined by how voters evaluate the benefits and the costs of sanctions. For example, poor voters are more likely to value the private benefits they receive from buying votes (Stokes 2005, 321-322). Among negative incentives such as sanctions for not voting, Trantidis lists financial sanctions such as denial of credit, discriminatory tax controls (125), and other retaliatory measures such as punishment through employment. Voters who happen to be in a more valuable socio-economic position are more likely to commit to fulfilling their part of the bargain.

When considering brokers, according to Stokes, Dunning, and Nazareno (2013), one of the factors influencing party choice is the magnitude of the broker's network. The party is interested in brokers with the larger network size because they can bring more voters. At the same time, larger networks create additional incentives for the rent-seeking behavior of brokers. An important implication that affects the actions of brokers is their rent-seeking behavior (Stokes et al., 2013). Since brokers are the main redistributors of party resources, their corresponding actions are not always fully responsible for the party's electoral victory. Aspinall (2014) shows that brokers with access to fewer resources, but with higher certainty about the candidate or party's chances of winning, are more likely to be loyal. Such models rely on the assumption that a broker with a larger network may be able to switch from one political party to another and use this as leverage when negotiating for resources (Camp 2017).

Another factor that determines the loyalty of brokers is their certainty that the candidate or party will win the election (Stokes, Dunning, and Nazareno 2013). The higher the probability that the candidate or party will win, the less effort the broker has to put in to achieve victory. Moreover, when more than one broker is involved in the constituency, the individual contributions are "noisy" and therefore do not create additional motivation for brokers to invest their efforts into bringing more votes (120-121).

However, non-democratic regimes are likely to impose certain constraints on clientelistic exchange. First, the very high probability that the dominant party or autocrat will win generates fewer incentives for both brokers and voters to try harder to deliver the desired outcome to politicians. For example, the decline in the effectiveness of the PRI's political machine in Mexico could be partly explained by the perceived predictability of election outcomes by both brokers and voters (Stokes, Dunning, and Nazareno 2013, 121). Second, the literature suggests that politicians are more likely to select brokers with personal ties to local elites (Brierley and Nathan 2021). In the case of the authoritarian state, it is likely that economic actors from medium or large business entities will have personal ties to political elites. In addition, as shown by Frye, Reuter, and Szakonyi (2014), authoritarian states tend to mobilize workers from larger firms because of the lower cost of voting. Thus, the party or candidate is more likely to reach out to brokers with bigger networks even though the effectiveness of smaller or denser networks is proven (Szwarcberg 2015).

In principle, the greater degree of control over the country's resources should provide the autocratic government with more leverage and available sanctions to control votes (Magaloni 2006). In practice, while control over turnout appears to be relatively easy to establish, control over personal votes requires significantly more resources and effort (Nichter 2008, Gans-Morse, Mazzuca, and Nichter 2014). Thus, while it is likely that voters in the autocratic state are subject to double persuasion to both show up at the polls and vote for the dominant party or autocrat, the possibility of controlling the vote is limited by the motivation and monitoring capacity of the intermediaries.

What is also important to consider is the motivation of the voters not to keep their side of the bargain and not to vote as requested under autocratic setting. First, they may simply have different political preferences, but without proper coordination there is no way to channel them into votes (Turchenko and Golosov 2023). Organized clientelistic exchange anecdotally could provide such mobilizing coordination, but with an unfavorable outcome for dominant party if not properly monitored. On the other hand, voters might punish politicians they associate with undermining democracy (Svolik 2021). They can do this by switching their votes to those parties or politicians they perceive as more democratic, either within the normal voting process with standard turnout, or with increased turnout resulting in protest voting, or with reduced turnout resulting in a corresponding decrease in the absolute number of votes (2-4).

Indeed, voter turnout buying in itself could be a strategy of particular interest to authoritarian regimes. As Magaloni (2006) describes in the case of Mexico, "...given that the elections were not competitive, high voter turnout was intended to generate a public signal about the strength of the regime, which was mainly intended to deter disaffected politicians from defecting to the ruling party" (4). Moreover, González-Ocantos et al. (2015) proved that voter turnout can be one of the main lines of competition between the opposition and the ruling party. If the opposition wants to jeopardize the elections, it can claim the boycott as a strategy to express its discontent. Furthermore, in an authoritarian context, voter turnout could be correlated with loyalty under certain conditions. For example, as shown by McAllister and White (2017), in Russia's remote regions, higher turnout would be correlated with higher United Russia election results, while in more urban regions, lower turnout would be positively correlated with United Russia results. This is due to the concentration of the opposition and the overall popularity of the incumbent party, which tends to be higher in rural areas. By demobilizing voters in places with less loyalty to the dominant party or autocrat, it is ensured that only the loyal group is aware of the elections and comes to vote.

The issue arises when the strategy of mobilizing a loyal segment of voters to participate in the election fails. This can happen due to challenges in aligning the targeted group to the required size, or inaccurately assessing the degree of loyalty within the group. As explained earlier, both the logic of clientelistic exchange (principal-agent dilemma) and the authoritarian regime (high probability of winning for incumbent and choosing brokers based on personal ties rather than effectiveness) condition politicians to certain types of clientelistic exchange, with all the limitations that this entails. Table 1 shows the possible outcomes of clientelistic strategies based on different incentives for the broker and the voter. It becomes evident that the most effective solution for the party or politician is to engage a broker with a smaller network size. This broker should evaluate the probability of winning as relatively low, which would motivate them to allocate more resources and efforts toward purchasing

Table 1: Electoral mobilization effectiveness in clientelistic exchange

				Broker's Network Size				
				Small		Big		
				Value of Benefits and Sanctions to Voters				
				High	Low	High	Low	
Probability of winning	High	Monitoring Regime	Low	Moderate	Ineffective	Ineffective	Ineffective	
			High	Effective	Moderate	Moderate	Ineffective	
	Low		Low	Effective	Moderate	Moderate	Moderate	
			High	Highly Effective	Effective	Effective	Moderate	

votes and increasing voter turnout. Simultaneously, the voter should highly prioritize the benefits and sanctions while having an efficient monitoring system in place to oversee their actions.

However, authoritarian regime conditions limit the potential effectiveness of clientelistic exchange. Since the broker is confident that the incumbent will win, and party members tend to hire brokers with larger networks, this automatically puts the political machine in the quadrant with the least effective outcomes. Only if both the monitoring system for voter behavior is highly effective and voters attach significant importance to benefits and sanctions can a moderate outcome be achieved. This implies that the party would attain an electoral result that is somewhat desirable.

Thus, this article hypothesizes that due to the constraints of both the regime's authoritarian nature and the principal-agent dilemma of clientelism, the outcome of clientelistic exchange achieves its goals only to a limited extent, primarily in those areas that can be controlled with varying degrees of effectiveness.

### 3 Model specification

Measuring the extent to which electoral mobilization through business actors benefits the regime (including an autocrat and the dominant party) is complex for several reasons. First, one must establish the presence of electoral mobilization. Although direct methods like surveys are available, they often require field access, which may not always be feasible, particularly in the Russian context. Fortunately, anomalies can still be detected indirectly. Building on the methodology used to identify electoral fraud, which involves examining distribution anomalies, this paper proposes analyzing changes in voter turnout in relation to factors believed to influence its levels. As such factor we propose looking at large companies'

geographic proximity. In addition, various controls are required to make sure the observed effect is related to proposed explanatory variable and not to other characteristics of locality, electoral committee or actors of electoral mobilization.

Second, the impact of electoral mobilization needs to be quantified. Assuming that the primary goal of electoral mobilization is to achieve either high voter turnout or a high vote share for the autocrat or dominant party—or both—these should be the outcome variables in the model. Regarding the unit of analysis, indirect measures do not permit examination of individual votes but rather at a somewhat aggregated level. In the Russian context, the first level of aggregation of individual votes is the results from local electoral committees. Although these results can, in principle, provide information about changes in voter turnout over the course of an election, our focus is on the final results within each election.

Building on the logic outlined in Table 1, we aim to investigate whether a) the regime indeed utilizes large companies as brokers for electoral mobilization; b) electoral mobilization actually occurs; and c) it results in a somewhat suboptimal outcome for the autocrat or dominant party. While some factors influencing this suboptimal outcome remain constant in each electoral cycle, such as the expected probability of victory for the party or autocrat, others vary. Hence the model tested in this paper could be represented by the following equation:

$$Y_{uik} = \beta_1 \text{proximity}_{uik} + \alpha_{j[uik]} + \delta_{k[uik]} + \beta_2 \text{committee population}_{uik} + \epsilon_{uik}$$

Where:

- $Y_{uik}$  is the dependent variable representing either the vote share for a particular party or candidate, or overall turnout at electoral committee  $uik$ .
- $\text{proximity}_{uik}$  is the explanatory variable representing the proximity of large firms to the electoral committee.
- $\alpha_{j[uik]}$  and  $\delta_{k[uik]}$  are the fixed effects for region  $j$  and market  $k$ , specific to each electoral committee.
- $\text{committee population}_{uik}$  represents the number of voters assigned to the electoral committee.
- $\epsilon_{uik}$  is the error term.

Based on the model and proposed theoretical framework, it is expected to observe a relationship between brokers with large networks (big companies) and electoral results of dominant party and incumbent at the respective local electoral committee. Hence we propose the following hypotheses to be tested:

- H1: Large companies in close proximity to an electoral committee increase voter turnout, suggesting the presence of electoral mobilization.
- H2: The proximity of large companies to a local electoral committee either does not enhance the vote share for the dominant party or incumbent, or it reduces it.

- H3: Large companies situated in smaller localities lead to both higher turnout and a greater vote share for the dominant party or incumbent.

If large companies do not engage in electoral mobilization, we anticipate no significant changes in voter turnout or vote share despite closer geographical proximity to electoral committees. After executing the models, we also perform robustness checks to determine whether other variables, such as salaries or sectors dependent on state involvement, significantly influence the effectiveness or presence of electoral mobilization. A more detailed explanation for robustness check models is presented in respective section of this paper. The hypotheses for these robustness checks are formulated as follows:

- H1: Large companies located near electoral committees contribute to electoral mobilization particularly when average salaries are low, indicating a higher dependence on income among voters.
- H2: Large companies located near electoral committees contribute to electoral mobilization particularly when average salaries are high, suggesting a potential for greater economic loss for employees.
- H3: Large companies that are part of state-dependent sectors and located near electoral committees are more actively involved in electoral mobilization.

## 4 Russian context

The regime of the Russian state in the period from 2012 to 2021 is considered by researchers as electoral authoritarianism (Beazer and Reuter 2022, Dollbaum 2020, Gel'man 2014, Sirotkina and Zavadskaya 2020). And yet it experienced a lot of fluctuations in electoral dynamics. One of the obvious lines of division is the difference in who is elected. Presidential elections versus parliamentary elections will have some similarities in terms of electoral manipulation used - such as adjusting turnout or using spoilers to split the opposition vote - but at the same time, parliamentary elections will require more strategic decisions and planning. Conversely, an alternative way to draw the dividing line is by considering time. Electoral authoritarianism, especially a relatively new one, goes through stages of consolidation and therefore experiences different levels of electoral support for the dominant party and the autocrat (Geddes, Wright and Frantz 2018). As a result, different mechanisms of electoral manipulation come into play.

The study covers four election cycles: two presidential campaigns in 2012 and 2018, and two federal parliamentary (Duma) campaigns in 2016 and 2021. The timeline includes major elections after Dmitry Medvedev's presidency and after the Bolotnaya movement. The reason for choosing such a timeline is the comparability within one of the periods of consolidation of Russian electoral authoritarianism, which could be characterized as "tightening the screws". The protests of 2011 caused by massive fraud in the Duma elections and dissatisfaction with the results, as well as the subsequent protests of 2012 with the ensuing criminal prosecution, can be considered one of the milestones in the development of Russian authoritarianism. As a result, we expect the post-2011 elections to be more comparable due to the changed

regime nature. At the same time, there are some differences and peculiarities of each election campaign.

The 2012 presidential election is the first election of interest for this study. The elections took place a few months after the 2011 protests, which were caused by massive electoral frauds in the Duma campaign. In response to the protest movement, some measures were introduced to ensure fairness, including videotaping of polling stations and installation of transparent ballot boxes (Kalinin 2016, 198). But, of course, the main issues, such as access to the media and administrative resources, continued to be unregulated or untouched. Moreover, this presidential campaign took place right after Medvedev's presidency and the agreement between the candidates (Medvedev announced his refusal to run for another term and proposed Putin instead at the United Russia party congress on September 24th of 2011). The general perception of this "castling" as a show with little electoral integrity or political fairness was quite common in public opinion (Levada 2011). At the same time, pre-election polls showed a somewhat pro-Putin majority (Levada 2012). Vladimir Putin won elections with 63.5% of votes and 65.3% turnout. Based on a statistical analysis of electoral fraud in various elections, it is observed that it ranges from 7 percentage points of all votes in major urban centers to about 15 percentage points across the country (Kalinin and Shpilkin 2012). The opposition had the usual set of candidates to choose from, with Vladimir Zuganov, a representative of the Communist Party, getting the second highest share of votes (17.2%) and Mikhail Prohorov, the only non-systemic opposition representative getting almost 8% of votes.

The 2018 presidential campaign took place in less volatile circumstances, and therefore produced even better results for Valdimir Putin. For the first time, the president won the elections with an actual majority of the population's votes (67.5% turnout with 76.7% share of votes or 56,202,497 votes). The usual main opponent from the systemic opposition - Gennadiy Zyuganov, a leader of the Communist Party - did not participate in the elections. Instead, the Communist Party was represented by Pavel Grudinin, who got the second best result (11.8%). Alexei Navalny, who planned to run for president and had collected all the necessary signatures, was not registered by the Central Election Committee. On the other hand, Xenia Sobchak, who was supposed to represent the non-systemic opposition, was heavily criticized for her alleged agreement with the Kremlin to divert votes from the opposition within the population. Supporters of Alexey Navalny tried to boycott the elections and thus reduce the turnout, with mixed results (Zavadskaya 2018). According to pollsters, the expected voter turnout was expected to reach 80%, but the actual turnout fell short of the triumphant expectations (VTsIOM 2018). At the same time, according to some estimates, the number of direct electoral frauds was relatively low (Meduza 2018).

The 2016 parliamentary elections were held for the first time in 13 years with a mixed parallel electoral system, where voters chose both a party and individual candidates, with half of the deputies coming from party lists and half from direct voting, both independent of each other. According to some estimates, direct voting favors the holders of administrative resources, and the proportional part, together with other added mechanisms (party fragmentation, electoral formulas, etc.), makes such an electoral system particularly advantageous for the dominant party (Golosov 2017). However, the 2016 Duma elections were not flawless for United Russia, as evidenced by a particularly low or strategically demobilized turnout, especially in areas of low support (McAllister and White 2017). With the lowest turnout

in the history of Russian Duma elections (47.8%, with some regions such as St. Petersburg showing turnout at the level of 32.5%), United Russia won the constitutional majority in the Duma with 343 out of 450 mandates, with the remaining seats distributed among the usual group of parties (KPRF, LDPR, and Just Russia). However, according to statistical estimates as well as observers' reports, the number of electoral frauds remained high, proving ballot stuffing and other forms of electoral manipulation (Kalinin 2017).

Finally, the 2021 parliamentary elections are the most extraordinary in the list. The most prominent part about them is the COVID-19 circumstances, which led to the most obscure mobile polling stations, almost impossible to monitor, as well as experiments with electronic voting. Another outstanding feature of these elections was three days of voting instead of one. According to some media reports, voters from government-affiliated organizations were invited to vote on the first day and then monitored by the turnout. If a person didn't show up, there were two more days to make sure that person actually voted (Meduza 2021). Nevertheless, turnout was not significantly higher than in 2016, at 51.7%, and United Russia's results were lower than in 2016, but still with a constitutional majority of 324 out of 450 seats. Among other parties winning seats in the parliament, the usual set of KPRF, LDPR and Just Russia was accompanied by the newly created New People party. Another important feature of these elections was the "smart voting" system, introduced by Alexey Navalny and his supporters. The app or website provided a voter with information about the candidates in the district who should be chosen over the United Russia candidate, among all the candidates who were registered. The initiative was not widely supported by other members of the opposition, and the app was blocked by Russian authorities, but according to some estimates, Smart Voting had a significant impact on the results of subnational elections (Golosov and Turchenko 2023). As usual, the number of direct electoral frauds was quite high, judging by the normality of vote distribution and turnout for the three days of voting (Novaya Gazeta, 2021).

All in all, while the Russian elections from 2012 to 2021 definitely had differences in the nature and extent of voter mobilization, all of them had voter turnout somewhat at the core of the chosen strategy, depending on prior expectations about the election results. The regime employs diverse strategies to influence voter turnout. Peisakhin et al. (2020) suggest that in electoral authoritarian systems, voter apathy renders traditional appeals for electoral mobilization less effective. This indicates that the regime must exert additional institutional or socio-economic pressures to mobilize voters. For instance, Saikonen (2017) demonstrates that socio-demographic characteristics of localities significantly affect mobilization levels. The study reveals that decreased electoral competitiveness correlates with increased mobilization efforts, linking higher turnout to agricultural employment and ethnic networks. Furthermore, the phenomenon of ethnic mobilization has been extensively studied and validated in the context of Russia by various scholars, including Goodnow et al. (2014), Minaeva and Panov (2023), and Shkel (2024). In more institutionalized settings of electoral mobilization, workplace mobilization emerges as a key strategy for the regime (Frye et al. 2014, p.196). Research indicates that companies with immobile assets are more likely to engage in the electoral mobilization of their employees due to their susceptibility to regulatory sanctions or expropriation (Ibid, p.213-214). Additionally, two primary forms of electoral mobilization have been identified: intimidation and vote buying. Voter intimidation tends to occur where vote buying is costly and employers wield significant control over their workers

(Frye et al. 2019). It is noted that in single-company towns with limited employment alternatives, voter intimidation is more prevalent. Conversely, more active forms of monitoring occur in environments where employers have less control over their employees (*Ibid*, p.878).

Indeed, due to the secrecy of the ballot and the limited extent to which voting behavior could be controlled, mobilization have variation in effectiveness. In the next section, we explain how the use of business firms for electoral mobilization was one of the preferred strategies, but we also analyze how effective it was in practice. The use of private actors as intermediaries in the clientelistic exchange had its limitations in terms of electoral outcome.

## 5 Data collection

Several sources were used to obtain the data for the analysis. First, it was necessary to have the data on election results disaggregated to the level of Local Electoral Committees (UIK).<sup>1</sup> The final sets of election results were collected from the Territorial Electoral Committees and Central Electoral Committee and include information on the 2012 and 2018 presidential elections and the 2016 and 2021 federal parliamentary elections. The data are stored at the level of Local Electoral Committees and include information on the number of votes per candidate or party, voter turnout, number of ballots of different types, as well as information on Local Electoral Committees (number of voters assigned to each, corresponding Territorial Committee, etc).

Secondly, the data on the location of Local Electoral Committees and their population were obtained from the INID (Infrastructure of Scientific-Research Data) project<sup>2</sup>. The data was collected from the website of the Central Electoral Committee and contains detailed descriptions of each of the Local Electoral Committees. In particular, it has the geographical coordinates of the electoral committees (longitude and latitude), as well as the approximate population living in the district with the assigned committee (n=93786).

Third, the data on all business entities operating in Russia were collected from the Federal Tax Service Open Data. The initial list contained 6,000,000 business entities with the corresponding number of employees, income and expenses. The list was then narrowed down

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<sup>1</sup>The electoral system of the Russian Federation includes four levels of voting, data collection and aggregation. The central level is a Central Electoral Committee (TsIK), which collects and processes votes from Regional Electoral Committees and receives the results from Territorial Electoral Committees (TIK). Territorial Electoral Committees usually represent several large municipalities and include several Local Electoral Committees (UIK). Local Electoral Committees are the lowest level of the electoral system in Russia. Local Electoral Committees collect results from polling stations (in the majority of cases, the location of the polling station and the location of the Local Electoral Committee are the same). After counting and checking the results, the Local Election Committee sends them to the Territorial Electoral Committee. The Territorial Electoral Committee is responsible for ensuring that the documents and final calculations are consistent and in accordance with the law. It is also responsible for any legal disputes or objections from observers. The Territorial Electoral Committee then enters the aggregated results into the GAS Vyborg electronic system, which is used by the Central Electoral Committee to calculate the final results. In addition, the Territorial Electoral Committee sends physical ballots to the Regional Electoral Committee, which then stores them. The Regional Electoral Committee is also responsible for legal disputes over election results and election fraud.

<sup>2</sup>Right now the project closed access to the data on their official website, but still published it via their official telegram channel

to include only non-individual entrepreneurship entities due to the availability of branch addresses as well as the accuracy of the legal address (private entrepreneurship entities provide only the city and region address). This list was further reduced to only large companies by a cumulative index, which combines income, expenses and number of employees of largest companies<sup>3</sup> in the region and market depending on the size of the population in a given locality. In other words, larger cities would have a greater number of companies selected, while smaller cities or villages are likely to have only a few per sector. Next, the addresses of the companies were assigned using the Dadata API service and the tax IDs of the companies. Branch and legal address information was also collected to ensure that actual locations were covered. Finally, the geocode (latitude and longitude) was assigned to each company using the Google API service.

Next, election results were matched to Local Electoral Committees geographic data using Local Electoral Committees IDs and place names. Next, the firm dataset was matched by the geographically closest distance between the local electoral committee and the large firm, calculated in meters using the vantage point tree approach. The final dataset contains 92875 observations (local electoral committees) with 22,600 unique firms (the distribution can be found in Appendix A). On average, there will be about four electoral committees located in close proximity to the same large company. This is reasonable because a single location may be divided into multiple electoral committees assigned to it. For example, a school might be divided in such a way that one part of it hosts one electoral committee, while the other part hosts another.

After removing the extreme outliers, the median distance between the Local Electoral Committee and a large enterprise in the data is 1700m. For the final sample this value was rounded to 2km and the electoral committees were narrowed to this distance from a large firm. Given the big variance in density of Local Electoral Committees per different localities, the median distance should roughly account for large cities and smaller locations.

## 6 Results

One of the important questions to be addressed in interpreting the data is whether the geographical distance between the companies and the electoral committees can be used to infer the relationship between them and the mobilization of workers. The main problem that arises here is that people may work and live in very distant places, and therefore, even if they have been induced to vote, the actual voting will take place in a different electoral committee than the one close to the company.

There are two arguments against this. The first is that before the 2018 presidential election, a new amendment was introduced that eliminated absentee ballots, which is a ballot you get to vote in a place other than your official registration. This meant that a person could have voted wherever they were without prior registration, eliminating the need to vote from their home address. Second, we argue that absentee ballots would be used more frequently in electoral stations close to large companies, and the mechanism of mobilizing voters for those who live farther from their workplaces would imply the use of such ballots.

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<sup>3</sup>the number of companies varied from 1 to 10 depending on the size of the locality

Figure 1: Violin plot distribution of absentee ballots

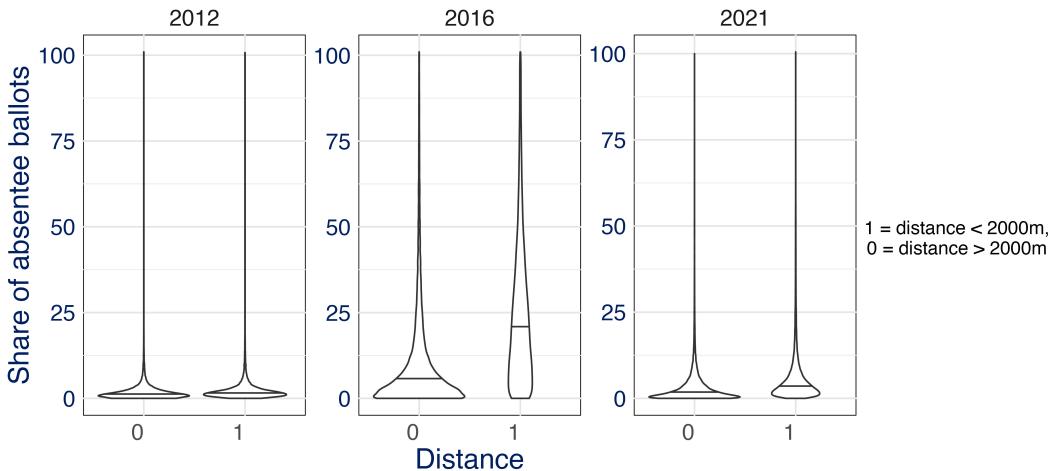
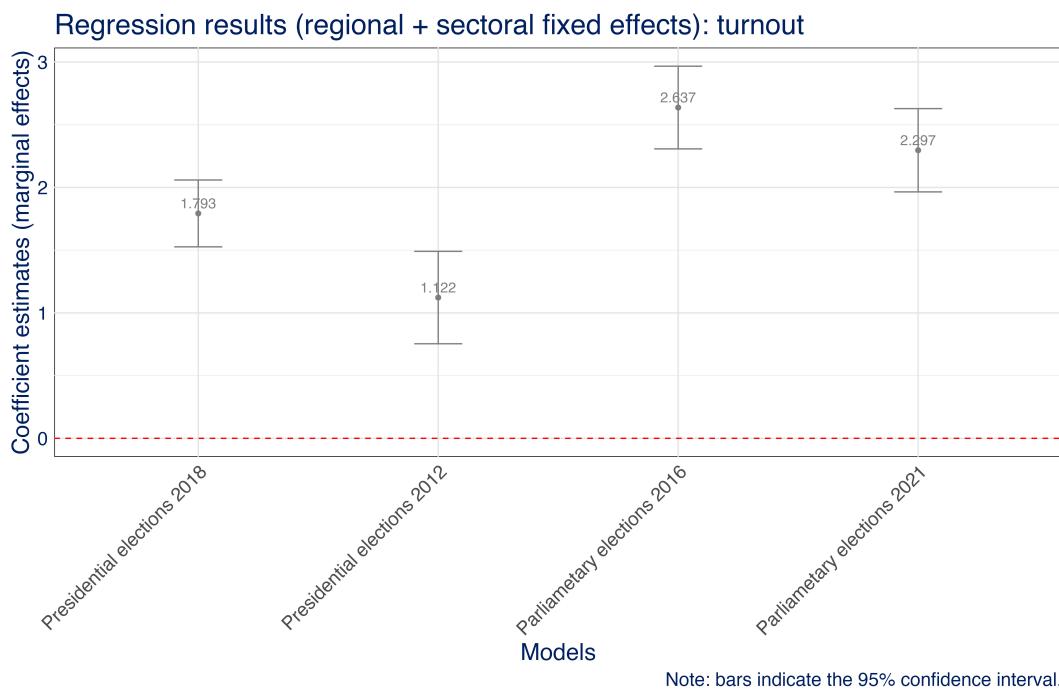


Figure 1 shows that the distribution of the share of absentee ballots in all ballots received by the committee over the years varies depending on the distance between the committee and the large business entity. The 2012 presidential election seems to be an exception - while there is a very small difference in the median value of absentee ballots, it could be negligible and the distribution looks very similar. In 2016 one can observe a drastic difference - electoral committees situated at a greater distance from a business entity exhibit an absentee ballot share of approximately 6%, whereas committees in close proximity can account for as much as one-fifth of all the ballots. In 2021, the medians have a smaller gap, but still some, and also show a different distribution - the absentee ballots share at electoral committees closer to the business entities is more concentrated around the median, with a longer tail toward a higher share. Therefore, for further analysis, it is suggested that the possible mechanism behind voter mobilization, especially in 2016, 2018 and 2021, could be through absentee ballots.

Subsequently, a panel regression model was employed to evaluate the association between geographical proximity and electoral outcomes. The choice of model implied controlling for possible variation within markets, regions, and the size of the population assigned to the Local Electoral Committee. Since the variation could have been explained by the specificities of certain sectors, as shown by Frye, Reuter and Szakonyi (2014), as well as by regional specificities (e.g., the density of large firms or the specialization of certain regions in certain sectors), it was important to ensure that neither the population itself nor the other possible unaccounted factors were the ones influencing the result. Therefore, the market and region two-ways fixed effects model was used, as well as controls included for the population size. Each model is robust to Newey-West Heteroskedasticity and Autocorrelation Consistent Estimators (Appendix C and D), as well to clustering standard errors at the company level.

The first model (full regression table results are presented in Appendix B) shows the relationship between the geographical proximity to the nearest large enterprise (derived from the distance measured in kilometers) and the overall turnout (in percentage) at the observed local electoral committee. Figure 2 shows that the relationship between the two is stable, significant, and positive. The legislative elections turnout seems to be affected to a slightly greater extent. In 2016 and 2021, with each additional kilometer of proximity, the turnout increased approximately by 2.6 and 2.3 percentage points, holding other variables constant. The turnout in the presidential elections of 2012 and 2018 was affected, with each additional kilometer leading to a higher turnout of 1.8 and 1.12 percentage points respectively.

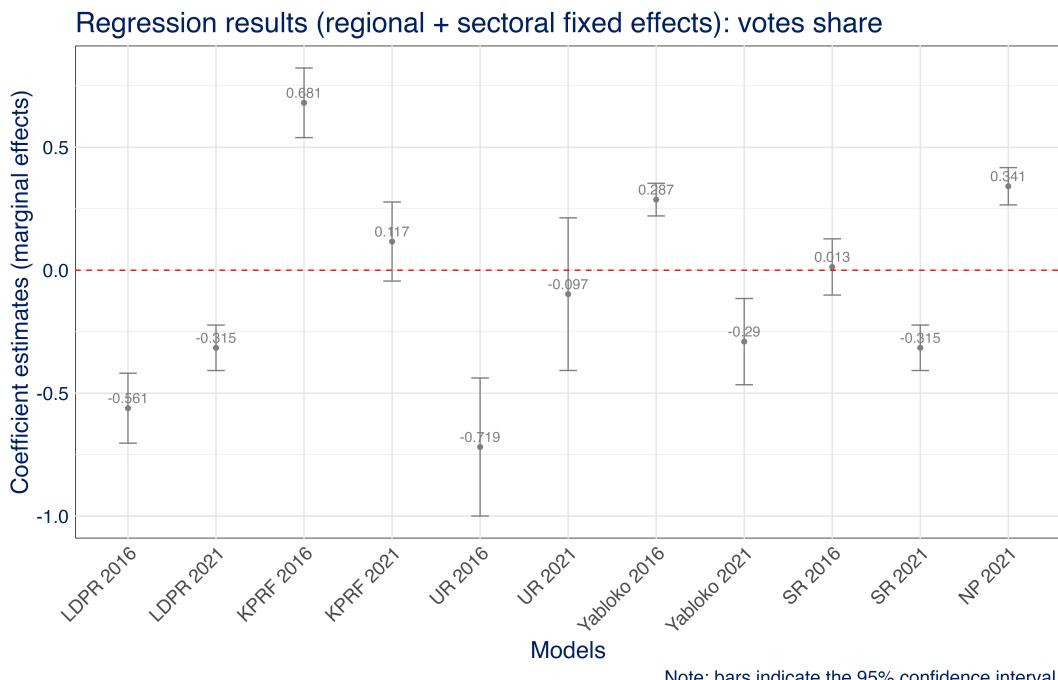
Figure 2: Effect of geographical proximity on turnout at presidential and parliamentary elections



However, while the increase in voter turnout is relatively expected, the actual distribution of votes to different candidates and parties is not obvious given the secrecy of the ballot. Figure 3 shows the effect of the geographic proximity of the nearest large business on the distribution of vote shares for different parties in the 2016 and 2021 Duma elections.

It appears that the increased turnout in both the 2016 and 2021 elections did not actually result in a higher vote share for United Russia. On the contrary, the parties that benefit from the presence of large companies in the proximity are KPRF and Yabloko in 2016, and the New People Party in 2021.

Figure 3: Effect of geographical proximity on vote share at parliamentary elections

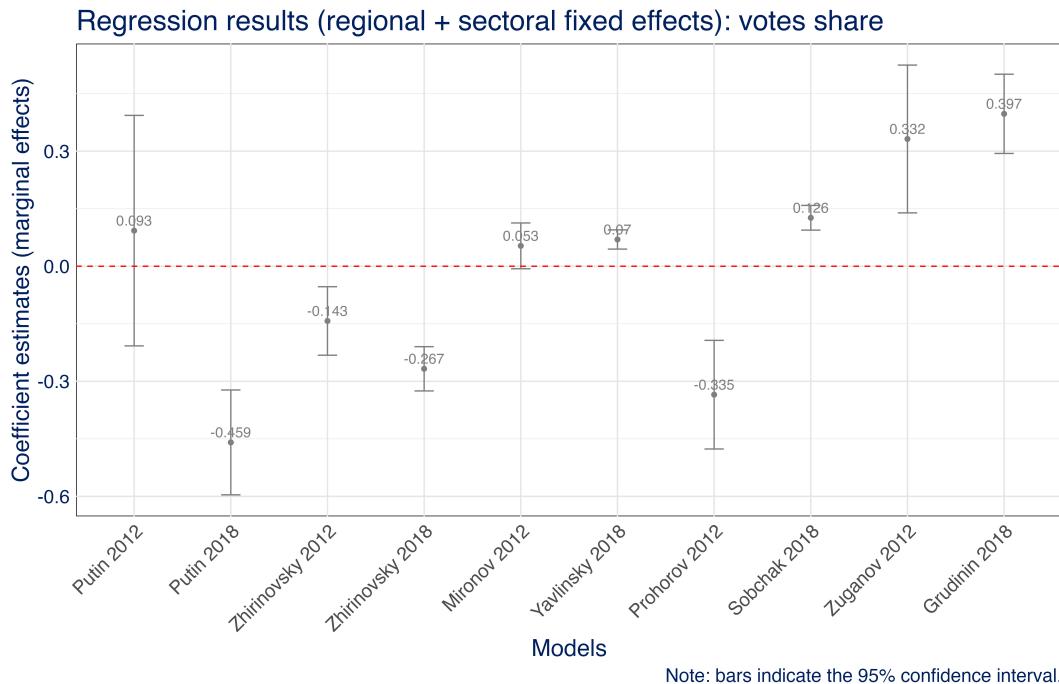


On the one hand, this is consistent with the expectation of the ineffectiveness of the clientelist system, in which brokers with large networks are involved, while monitoring capacities are low and the probability of victory of the dominant party is high. On the other hand, this finding sheds light on the voters' side of this bargain. It seems that voters affected by electoral mobilization voted for the parties they most associated with "protest voting" or more or less real "opposition". In 2016, the LDPR seems to be the party that voters definitely wouldn't choose from the opposition instead of United Russia, expecting the Communists or Yabloko to be a better option. In 2021, this effect goes fully to the New People party, which, regardless of being allegedly a spoiler agreed by the Kremlin, attracted a lot of protest votes.

Turning to presidential election results, Figure 4 shows the model that evaluates the relationship between geographic proximity and vote share for different candidates in the 2012 and 2018 elections. The general tendency of vote shares for Putin in 2012 and 2018 seems to follow a similar pattern - voter mobilization in 2018 resulted in fewer votes for Vladimir Putin, with each additional kilometer of proximity to large companies resulting in 0.5% lower vote share for the incumbent. Similarly, in 2012, higher turnout did not result in higher vote share for Putin.

At the same time, it appears that in 2012, Sergey Mironov (at 90% significance) and Gennadiy Zuganov were the candidates who benefited the most from the close proximity of large companies and the subsequent increase in voter turnout. For every kilometer closer

Figure 4: Effect of geographical proximity on vote share at presidential elections



to these companies, their support increased by 0.05 and 0.33 percentage points respectively. In the 2018 election, three other candidates, Xenia Sobchak, Grigorij Yavlinski and Pavel Grudinin, emerged as the primary beneficiaries of electoral mobilization. Similar to the 2012 election, the Communist candidate benefited the most from voter mobilization, gaining 0.4% for every kilometer increase in distance.

Overall, the results of the analysis tell two stories. The first story is about voter mobilization, which has been shown to occur systematically in both parliamentary and presidential elections in Russia from 2012 to 2021. The main added value to the findings of Frye, Reuter, and Szakonyi (2014) is that firm size, measured by economic activity and number of employees, is a strong predictor, controlling for all sectors. There are two plausible explanations for this phenomenon. First, it suggests that the critical factor at play is the administrative capacity of the firm, rather than the extent to which employees are dependent on their jobs. The presence of a large workforce and a high level of economic activity may indicate the existence of a more sophisticated administrative structure, with managers and teams that can be organized more effectively. Second, it is possible that the significant economic entities in each locality need to establish relational ties with the local administration, bureaucracy, and other government bodies where representatives of the United Russia party hold sway. This could be either to facilitate their economic activities or to maintain favorable relations with those in positions of authority. Such relationships could entail favors from both sides,

and helping party members or local politicians with electoral mobilization could be one of them.

The second story suggested by the results is about voter behavior, which may be quite different from what is expected from the electoral mobilization organized by the local political establishment. Not only United Russia and Vladimir Putin do not benefit from the electoral mobilization, but their opponents tend to get additional "protest votes". As was shown in the theoretical part of this article, the large network size of the broker - in this case a company - as well as the high probability of victory of the party or candidate already puts authoritarian politicians trying to organize clientelistic exchange in an unfavorable position. The quality of the monitoring regime, as well as the value of benefits and sanctions for voters, are the decisive factors in determining whether clientelistic exchange would be somewhat effective or not.

The latter two factors could be determined by the ability of the firm to break the secrecy of the ballot and the existence of mechanisms to punish voters for the "wrong" choice. To further test whether these two factors predict the results of the ruling party or the incumbent versus the results of other opposition parties and other candidates, the interaction effect between the size of the electoral committee and the geographical distance was added to see if the effect of distance changes when it comes to smaller electoral committees (which is potentially correlated with regional characteristics, hence regional fixed effects are removed from the model to avoid overestimating the predictor).

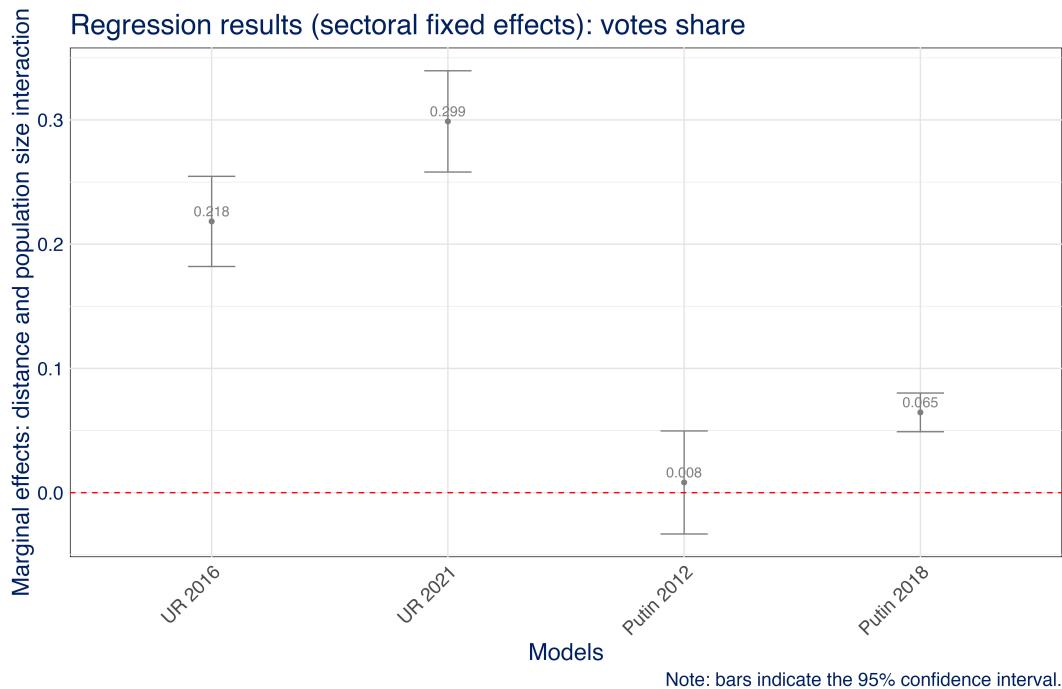
We believe that the size of the electoral committee could serve as a proxy for the monitoring regime and the value of sanctions and benefits to voters for the following reasons. First, smaller size quite often implies rural areas where personal ties are stronger and informal institutions prevail. Second, the number of observers is significantly higher in large cities than in smaller localities, which makes it easier to intervene in the electoral process and either allow direct fraud or control voters' choices. Finally, a smaller location also means a smaller market and a narrower choice of work opportunities, hence higher job dependency and more influence of employers over voters.

Figure 5 shows that the interaction effect between distance and size of the campaign committee (in hundreds) does exactly what is expected - it reverses the coefficients for United Russia and Vladimir Putin. Now, the decrease in proximity with the increase in the size of the population assigned to the electoral committee decreases the vote share (although the 2012 presidential election doesn't show significant results). This suggests that, when considered together, proximity to firms organizing voter mobilization actually benefits the dominant party and incumbent when there are fewer voters located assigned to a given committee, hence the locality is smaller.

## 7 Robustness checks

Several alternative explanations exist for the observed impact of distance on electoral outcomes at local electoral committees. Although the model accounts for market and regional variations, it may overlook some factors at a more granular level of analysis. For instance, salary levels could significantly influence voter behavior. A plausible theory is that voters with higher incomes—potentially linked to working for larger companies—tend to be more

Figure 5: Effect of geographical proximity and electoral committee size interaction on vote share at parliamentary and presidential elections



politically engaged and less supportive of the current regime (somewhat similar logic was explained in Minaeva and Panov 2023). Alternatively, one could assume that lower salaries create higher dependency on the employer, hence making electoral mobilization more plausible. Such argument follows a well-established tradition of seeing clientelism tightly related to poverty (Diaz-Cayeros et al. 2016). Consequently, it can be expected that election turnout and voting patterns might reflect voters' socio-economic status rather than the effects of electoral mobilization.

To examine this hypothesis, average salaries have been incorporated into the analysis. Unfortunately, a good quality nationwide data on average salaries across all Russian companies is unavailable. However, we do have access to data on average salaries at the city level<sup>4</sup>. Should there be a correlation between salary levels and voting behavior, it would be observable across different income groups within cities. Hence, we suggest dividing each model into four separate models, each corresponding to one of the quartiles of the city's average salary level. Analyzing the models within these groups will reveal whether any particular salary

<sup>4</sup>The Federal State Statistics Service data was used for this purpose, collected and cleaned by Center of Advanced Governance, INID project. URL: <https://data.rcsi.science/data-catalog/datasets/187/#dataset-codebook>. The data has time limitations, since it does not cover period after 2019. Therefore 2021 parliamentary elections are not included

group shows significant deviations from the original model.

The results are detailed in Annex E and F for election turnout and Annex G and H for vote share. Analyzing the presidential elections of 2012 and 2018, we observe that in 2018, the effects align with the primary model, whereas in 2012, proximity does not significantly influence turnout among the 1st and 4th quartiles of city average salary. This indicates that in 2012, individuals with the lowest and highest salaries did not alter their voting behavior based on the proximity of large companies. Furthermore, during the 2016 parliamentary elections, the data show that the group with the lowest average salary was unaffected by the proximity of companies, while other salary groups behaved in accordance with the primary model. One possible explanation for the observed effect in 2012 is an adjustment to the model, primarily because average salary data is unavailable for many cities. This results in a bias where larger cities are better represented in the data, and limitations in data lead to the exclusion of electoral committee population size control from the 2012 model. This exclusion allows for more variation and causes a shift in the coefficient. Alternatively, it could suggest that while electoral mobilization during the parliamentary elections of 2016 and the presidential election of 2018 was effective for population groups in higher salary quartiles, it had little or no impact on individuals in the lowest quartile during the 2016 parliamentary elections. This observation proposes a hypothesis that higher income levels increase the stakes and influence of electoral inducements on voters. On the other hand, in 2012, neither the lowest nor the higher salary quartiles showed a significant relationship with proximity to large firms. This lack of correlation could potentially be attributed to city bias—higher average salaries tend to occur in larger or more diverse cities where there are more workplace options. Conversely, lower salaries suggest reduced leverage over employees.

When examining vote share results, the overall pattern aligns with the main models, albeit with some variations. For instance, in the 2012 presidential elections, the main model shows that Putin's coefficients are insignificant, which is also true for the salary quantiles models, except for the second salary quantile (average and below-average salaries). For Prokhorov, without population control by the electoral committee and with a model accounting for heterogeneous effects, the results change significantly, leading to better electoral outcomes for him. Meanwhile, Zhirinovsky's results are insignificant for both the lowest and highest salary quartiles. All of these findings for 2012 presidential elections are somewhat consistent with the turnout model, suggesting that electoral mobilization, if it occurs, follows the expected logic—boosting turnout and effectively increasing votes for the opposition, particularly among middle-income groups.

Regarding the parliamentary elections of 2016, the results are most robust when analyzing the data by salary groups. Although the coefficient for the highest salary quartile becomes less intense, it remains significant and negative, similar to the pattern observed with LDPR. In this model, electoral mobilization continues to benefit opposition parties across all salary levels. For the presidential elections of 2018, both the original and the salary-based models display negative coefficients for Putin and Zhirinovsky and positive ones for other candidates. However, the effect for Putin and Grudinin becomes less significant as average salary quartiles increase. This indicates that economic factors play a role in the mobilization for presidential elections, particularly in terms of vote share. In 2018, while the turnout effect is consistent across different salary levels, higher salaries correlate with an insignificant impact on Putin's vote share, yet there is no positive correlation between turnout and pro-Putin votes.

An alternative explanation could also involve the type of company—whether it is state-owned or private, following the argument provided by Frye et al. (2014). The main model incorporates market fixed effects to account for variation across markets. To refine the assessment, we introduce two binary variables for sectors characterized as state-owned. One variable adopts a more conservative approach, identifying markets with 50% or more state ownership. The other variable takes a more relaxed stance, considering state ownership of 20% or more<sup>5</sup>. The results of these interacted models are detailed in Annex I and J. Regarding voter turnout, it appears that the interaction effect of proximity and state-owned markets (both variables have baseline category =0 ) diminishes the significance of the coefficients, leaving only the conservative state-ownership variable significantly negative for the 2021 parliamentary elections. This suggests that large state-owned enterprises on average do not lead to higher voter turnout when they are in closer proximity, implying some other mechanism in place. In fact, in 2021, the effect appears to be reversed, indicating that private companies may be the ones engaging in electoral mobilization, if at all.

## 8 Conclusion

This research had several goals. First, it aimed to prove that business actors are directly involved in the clientelistic mechanisms organized by the dominant party and local political actors in Russia. Additionally, it was crucial to demonstrate that this level of involvement was not exclusive to super-large businesses but extended to any relatively substantial economic entity within the local community. Second, this research aimed to shed light on the results of such electoral mobilization. Examining workplace electoral mobilization through the lens of a clientelistic structure (party - broker - voter) reveals some unique characteristics. In this scenario, brokers do not fit the classic mold of "professional" brokers who actively participate in a party's political activities and systematically organize political processes. Instead, brokers in this context are primarily businesspeople who are mostly concerned with the economic affairs of their companies. Their role as intermediaries in clientelistic exchanges is secondary.

Finally, this research aimed to challenge the prevailing belief that under authoritarian regime conditions, the dominant party and the incumbent necessarily achieve optimal electoral outcomes. In contrast, the assumption that the dominant party and the incumbent are always expected to win, along with the strategy of selecting brokers, places the ruling party in unfavorable circumstances for effective clientelistic exchange. Therefore, it is primarily up to the monitoring capacity to prevent voter mobilization from leading to protest voting. Since monitoring capacities are limited, more blatant cases of electoral fraud and "drying up" of voter turnout come into play.

Protest voting in the case of electoral mobilization is a topic worthy of further study. While it appears that voters are able to realistically assess the risks and benefits associated with their voting choices, it is important to ask whether this is due to their actual experience

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<sup>5</sup>According to the 2018 report by the Center for Strategic Research, such sectors include transportation (80%), energy supply (71%), natural resource extraction (70%), insurance and finance (47%), utilities (32%), mechanical engineering (31%), and media (23%). Source: <https://www.csr.ru/upload/iblock/6b5/6b5e2cd8d71d5d8e47662562b6e0d665.pdf>

of election monitoring or their anticipation and strength of informal agreements. Another factor that could potentially affect the results of this study is the number and type of electoral frauds registered in each of the local electoral committees. The reason for the better performance of United Russia and the incumbent in smaller localities may not only reflect genuine voting behavior, but may also be due to the relative ease of organizing fraudulent activities due to the limited presence of observers. Yet an inherent problem with fraud data is its reliance on observer reports, which introduces a bias toward larger localities where media attention and the availability of observers from different parties are more pronounced.

Ultimately, a more important question arises: why does a resourceful authoritarian regime like Russia opt for a clientelistic structure that relies on non-professional brokers whose primary expertise lies outside the electoral organization? It seems that the dominant party, as well as the incumbent, primarily uses the existing social, territorial, and economic structures to achieve desirable electoral results, but as this study has shown, they do not necessarily serve as such. In light of these findings, it remains important to further investigate the complexities surrounding the choice of a clientelism structure in authoritarian regimes like Russia, and the implications it holds for electoral outcomes.

## References

- Aspinall, E. (2014). When brokers betray: Clientelism, social networks, and electoral politics in Indonesia. *Critical Asian Studies*, 46(4), 545–570.
- Baidakova, A. (n.d.). Real'no 'Yedinuyu Rossiyu' podderzhali 15% izbirateley. Fizik Sergey Shpil'kin ob" yasnayet, kak anomal'nye skachki yavki vydavut fal'sifikatorov na proshed-shikh vyborakh — Novaya gazeta.
- Bakan, J. (2012). *The corporation: The pathological pursuit of profit and power*. Hachette UK.
- Baland, J.-M., & Robinson, J. A. (2008). Land and power: Theory and evidence from Chile. *American Economic Review*, 98(5), 1737–1765.
- Beazer, Q. H., & Reuter, O. J. (2022). Do authoritarian elections help the poor? Evidence from Russian cities. *The Journal of Politics*, 84(1), 437–454.
- Berenschot, W., & Aspinall, E. (2020). How clientelism varies: Comparing patronage democracies. *Democratization*, 27(1), 1–19. <https://doi.org/10.1080/13510347.2019.1645129>
- Bertrand, M., Kramarz, F., Schoar, A., & Thesmar, D. (2007). Politicians, firms and the political business cycle: Evidence from France. *Unpublished working paper, University of Chicago*, 1–40.
- Brierley, S., & Nathan, N. L. (2021). The connections of party brokers: Which brokers do parties select? *The Journal of Politics*, 83(3), 884–901.
- Camp, E. (2017). Cultivating effective brokers: A party leader's dilemma. *British Journal of Political Science*, 47(3), 521–543.
- Cox, G. W., & Kousser, J. M. (1981). Turnout and rural corruption: New York as a test case. *American Journal of Political Science*, 646–663.
- Dollbaum, J. M. (2020). Protest trajectories in electoral authoritarianism: From russia's "For fair elections" movement to alexei navalny's presidential campaign. *Post-Soviet Affairs*, 36(3), 192–210.
- Frye, T., Reuter, O. J., & Szakonyi, D. (2014). Political Machines at Work Voter Mobilization and Electoral Subversion in the Workplace. *World Politics*, 66(2), 195–228. <https://doi.org/10.1017/S004388711400001X>
- Frye, T., Reuter, O. J., & Szakonyi, D. (2019). Hitting them with carrots: Voter intimidation and vote buying in Russia. *British Journal of Political Science*, 49(3), 857–881.
- Gandhi, J., & Lust-Okar, E. (2009). Elections under authoritarianism. *Annual review of political science*, 12, 403–422.
- Gans-Morse, J., Mazzuca, S., & Nicther, S. (2014). Varieties of clientelism: Machine politics during elections. *American Journal of Political Science*, 58(2), 415–432.
- Geddes, B., Wright, J. G., & Frantz, E. (2018). *How dictatorships work: Power, personalization, and collapse*. Cambridge University Press.
- Gel'man, V. (2014). The rise and decline of electoral authoritarianism in Russia. *Demokratizatsiya*, 22(4).
- Golosov, G. V. (2017). Authoritarian learning in the development of russia's electoral system. *Russian Politics*, 2(2), 182–205.
- Golosov, G. V. (2021). The september 2021 duma elections: Mission overdone? *Russian Analytical Digest*, (271), 2–4.

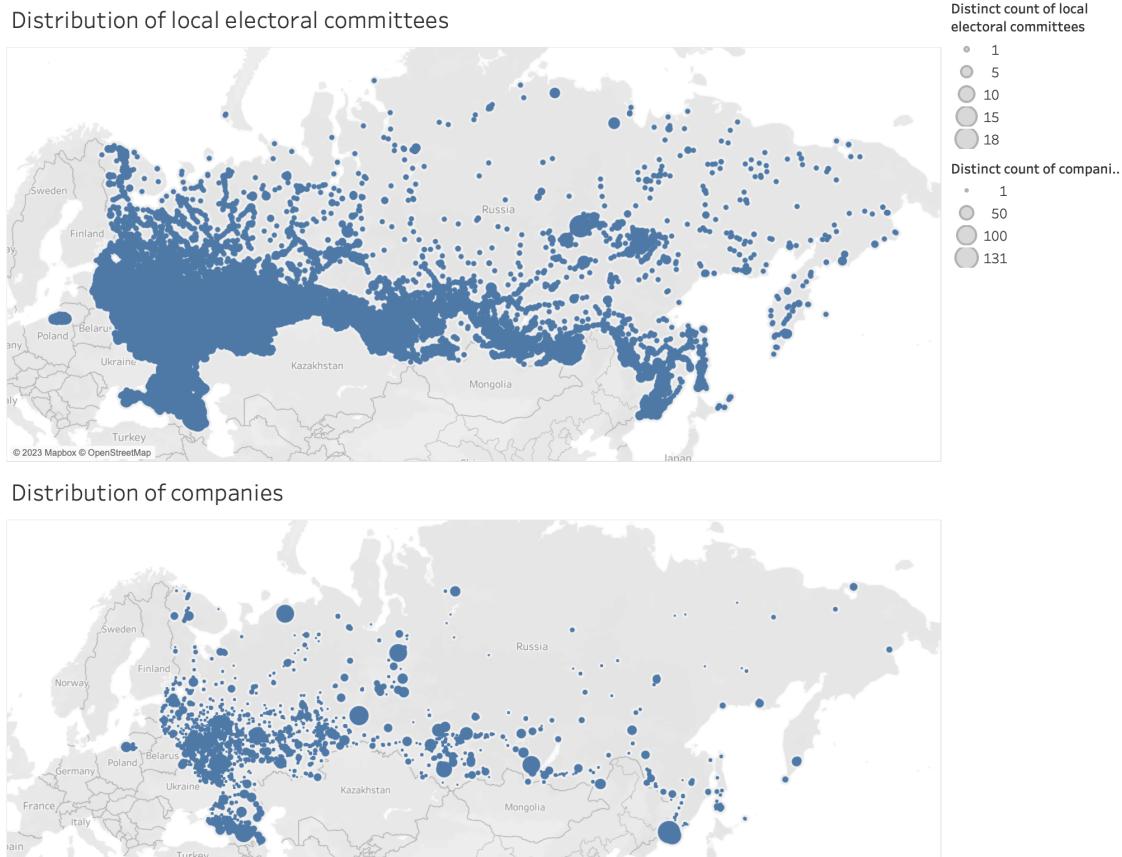
- González, F., & Prem, M. (2018). The value of political capital: Dictatorship collaborators as business elites. *Journal of Economic Behavior & Organization*, 155, 217–230.
- González-Ocantos, E., Kiewiet de Jonge, C., & Nickerson, D. W. (2015). Legitimacy buying: The dynamics of clientelism in the face of legitimacy challenges. *Comparative Political Studies*, 48(9), 1127–1158.
- Gonzalo, F. M. (2013). Forced labor, public policies, and business strategies during Franco's dictatorship: An interim report. *Enterprise & Society*, 14(1), 182–213.
- Goodnow, R., Moser, R. G., & Smith, T. (2014). Ethnicity and electoral manipulation in Russia. *Electoral studies*, 36, 15–27.
- Guriev, S., & Sonin, K. (2009). Dictators and oligarchs: A dynamic theory of contested property rights. *Journal of Public Economics*, 93(1-2), 1–13.
- Hart, D. M. (2004). "Business" is not an interest group: On the study of companies in american national politics. *Annual Review of Political Science*, Vol 13, 7, 47–69.
- Holland, A. C., & Palmer-Rubin, B. (2015). Beyond the machine: Clientelist brokers and interest organizations in Latin America. *Comparative Political Studies*, 48(9), 1186–1223.
- Huang, D., & Chen, M. (2020). Business Lobbying within the Party-State: Embedding Lobbying and Political Co-optation in China. *The China Journal*, 83, 105–128. <https://doi.org/10.1086/705933>
- INID project (Infrastruktura Nauchno-Isskovedatelskih Dannyh). (n.d.).
- Kalinin, K. (2016). The social desirability bias in autocrat's electoral ratings: Evidence from the 2012 Russian presidential elections. *Journal of elections, public opinion and parties*, 26(2), 191–211.
- Kalinin, K. (2017). *The essays on election fraud in authoritarian regimes* [Doctoral dissertation].
- Kalinin, K., & Shpilkin, S. (2012, March). Kompleksnaya diagnostika fal'sifikatsiy na rossiyskikh prezidentskikh vyborakh 2012 goda.
- Kamrava, M. (2017). State-Business Relations and Clientelism in Qatar. *Journal of Arabian Studies*, 7(1), 1–27. <https://doi.org/10.1080/21534764.2017.1288420>
- Karcher, S., & Schneider, B. R. (2013). Business politics in latin america: Investigating structures, preferences, and influence 1. In *Routledge handbook of latin american politics* (pp. 273–284). Routledge.
- Kim, W., & Gandhi, J. (2010). Coopting workers under dictatorship. *The Journal of Politics*, 72(3), 646–658.
- Kitschelt, H., & Wilkinson, S. I. (2007). *Patrons, clients and policies: Patterns of democratic accountability and political competition*. Cambridge University Press.
- Larreguy, H., Montiel Olea, C. E., & Querubin, P. (2017). Political brokers: Partisans or agents? Evidence from the Mexican teachers' union. *American Journal of Political Science*, 61(4), 877–891.
- Levada Center, A. C. (2011, October). Vladimir Putin i ego tretiy srok.
- Levada Center, A. C. (2012, March). VYBORY 2012 V OTSENKAH ROSSIYAN I PER-SPEKTIVY SLEDUYUSHCHIKH 12 LET.
- Lewis, D. (2012). Understanding the authoritarian state: Neopatrimonialism in Central Asia. *Brown J. World Aff.*, 19, 115.

- Magaloni, B. (2006). *Voting for autocracy: Hegemonic party survival and its demise in Mexico* (Vol. 296). Cambridge University Press Cambridge.
- Mares, I., & Young, L. (2019). Varieties of clientelism in Hungarian elections. *Comparative Politics*, 51(3), 449–480.
- Mares, I., & Zhu, B. (2015). The production of electoral intimidation: Economic and political incentives. *Comparative Politics*, 48(1), 23–43.
- McAllister, I., & White, S. (2017). Demobilizing voters: Election turnout in the 2016 Russian election. *Russian Politics*, 2(4), 411–433.
- Medina, L. F., & Stokes, S. (2007). Monopoly and monitoring: An approach to political clientelism. *Patrons, clients, and policies*, 68–83.
- Mikhail, Z. (n.d.). Vybory prezidenta — 2018. Glavnoe Rekordnoe golosovanie za Putina, 'zachistka' izbiratelyey i 'vtoroy referendum' v Krymu.
- Minaeva, E., & Panov, P. (2023). Dense networks, ethnic minorities, and electoral mobilization in contemporary Russia. *Problems of post-communism*, 70(4), 376–387.
- Nichter, S. (2008). Vote buying or turnout buying? Machine politics and the secret ballot. *American political science review*, 102(1), 19–31.
- Pedreira Campos, P. H. (2021). Building the dictatorship: Construction companies and industrialization in Brazil. *Big Business and Dictatorships in Latin America: A Transnational History of Profits and Repression*, 63–89.
- Peisakhin, L., Rozenas, A., & Sanovich, S. (2020). Mobilizing opposition voters under electoral authoritarianism: A field experiment in Russia. *Research & Politics*, 7(4), 2053168020970746.
- Po dannym 'Meduzy,' byudzhetnikov poprosili progolosovat' do poludnya. (n.d.).
- Rundlett, A., & Svolik, M. W. (2016). Deliver the vote! Micromotives and macrobehavior in electoral fraud. *American Political Science Review*, 110(1), 180–197.
- Saikkonen, I. A. (2017). Electoral mobilization and authoritarian elections: Evidence from post-Soviet Russia. *Government and Opposition*, 52(1), 51–74.
- Shkel, S. (2024). Chained by one chain: Mechanisms of electoral mobilization at the local level in the ethnic republics of Russia. *Problems of Post-Communism*, 71(1), 59–70.
- Shpilkin, S. (n.d.). Shpil'kin: 'Yedinaya Rossiya' poluchila 14 mln 'anomal'nykh' golosov. Bez fal'sifikatsiy 'partiya vlasti' nabiraet 31-33% — Novaya gazeta.
- Sirotkina, E., & Zavadskaya, M. (2020). When the party's over: Political blame attribution under an electoral authoritarian regime. *Post-soviet affairs*, 36(1), 37–60.
- Stephan, M. (2021). A typology of the collaboration between multinational corporations, home governments, and authoritarian regimes: Evidence from German investors in Argentina. In *Big Business and Dictatorships in Latin America: A Transnational History of Profits and Repression* (pp. 237–261). Springer.
- Stokes, S. C. (2005). Perverse accountability: A formal model of machine politics with evidence from Argentina. *American political science review*, 99(3), 315–325.
- Stokes, S. C., Dunning, T., & Nazareno, M. (2013). *Brokers, voters, and clientelism: The puzzle of distributive politics*. Cambridge University Press.
- Svolik, M. (2021). Voting against autocracy. Available at SSRN 3847894.
- Szwarcberg, M. (2015, July). *Mobilizing Poor Voters: Machine Politics, Clientelism, and Social Networks in Argentina*. Cambridge University Press.
- Trantidis, A. (2015). Clientelism and the classification of dominant party systems. *Democratization*, 22(1), 113–133.

- Turchenko, M., & Golosov, G. V. (2023). Coordinated voting against the autocracy: The case of the ‘smart vote’ strategy in Russia. *Europe-Asia Studies*, 75(5), 820–841.
- V pervyy den’ golosovaniya na vyborakh v Gosdumu na uchastkakh voznikli anomal’nye ocheredi. (n.d.).
- VCIOM, N. (2018, February). Vybory prezidenta Rossii-2018: Za mesyats do dnya golosovaniya.
- Wang, Q., & Jap, S. (2017). Benevolent dictatorship and buyer-supplier exchange. *Journal of Business Research*, 78, 204–216.
- Weiss, M. L. (2020). Duelling networks: Relational clientelism in electoral-authoritarian Malaysia. *Democratization*, 27(1), 100–118.
- Wright, J. (2011). Electoral spending cycles in Dictatorships. *Manuscript, Pennsylvania state university*, 32.
- Zavadskaya, M. (2018). The fight for turnout: Growing personalism in the Russian presidential elections of 2018. *Russian Analytical Digest*, 26(217), 2–5.

## A Distribution of observations

Figure 6: Distribution of observations: Local Electoral Committees and large enterprises.



## B Regression tables

Table 2: Regression results (regional + sectoral fixed effects): turnout

	<i>Dependent variable:</i>			
	Pres 2018 (1)	Pres 2012 (2)	Parl 2016 (3)	Parl 2021 (4)
proximity	1.793*** (0.136)	1.122*** (0.188)	2.637*** (0.168)	2.297*** (0.169)
as.factor(region)Yamalo-Neneckij avtonomnyj okrug	25.616*** (0.849)	35.931*** (3.477)	29.351*** (1.047)	25.946*** (1.083)
as.factor(region)Amurskaya oblast	-8.945*** (0.923)	3.497** (1.229)	-3.145** (1.137)	-1.706 (1.168)
as.factor(region)Arhangelskaya oblast	-7.105*** (0.844)	-3.662*** (1.018)	-7.077*** (1.045)	2.228* (1.066)
as.factor(region)Yaroslavskaya oblast				-1.285 (0.878)
as.factor(region)Astrahanskaya oblast	-7.372*** (1.039)	-4.890*** (1.368)	-4.409*** (1.280)	4.429*** (1.318)
as.factor(region)Belgorodskaya oblast	-1.593* (0.799)	9.454*** (0.971)	9.707*** (0.985)	10.522*** (1.008)
as.factor(region)Bryanskaya oblast	9.177*** (0.815)	1.822 (0.982)	7.342*** (1.005)	26.423*** (1.032)
as.factor(region)Čečenskaya Respublika	19.064*** (1.149)	39.845*** (1.396)	57.420*** (1.424)	59.865*** (1.434)
as.factor(region)Čelyabinskaya oblast	-0.733 (0.491)	-2.617*** (0.569)	-0.751 (0.605)	7.815*** (0.626)
as.factor(region)Čukotskij avtonomnyj okrug	14.197*** (2.982)	19.118*** (3.423)	12.953*** (3.665)	14.287*** (3.810)
as.factor(region)Čuvašskaya Respublika - Čuvašiya	-1.209	2.260	4.317***	7.114***

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(region)Evrejskaya avtonomnaya oblast	(0.841) −1.321 (1.649)	(2.151) −0.304 (1.894)	(1.038) 0.773 (2.027)	(1.062) 20.886*** (2.106)
as.factor(region)gorod Moskva	−4.266*** (0.555)		−2.653*** (0.686)	2.973*** (0.704)
as.factor(region)gorod Sankt-Peterburg	−0.186 (0.576)		−7.464*** (0.710)	2.847*** (0.731)
as.factor(region)gorod Sevastopol	12.496*** (1.295)		13.357*** (1.508)	16.589*** (1.563)
as.factor(region)Habarovskij kraj	−3.784*** (0.848)	0.141 (1.036)	−5.127*** (1.046)	6.262*** (1.071)
as.factor(region)Irkutskaya oblast	−10.634*** (0.671)	−5.388*** (0.814)	−10.255*** (0.828)	−2.375** (0.849)
as.factor(region)Ivanovskaya oblast	−11.604*** (0.765)	−2.276* (0.943)	−9.543*** (0.943)	−3.949*** (0.967)
as.factor(region)Kabardino-Balkarskaya Respublika	25.185*** (1.260)	16.323*** (1.560)	51.998*** (1.555)	49.455*** (1.583)
as.factor(region)Kaliningradskaya oblast	−6.736*** (0.793)	−3.904*** (0.971)	−0.701 (0.978)	4.685*** (1.002)
as.factor(region)Kalužskaya oblast	−1.389 (0.860)		−4.315*** (1.062)	3.708*** (1.087)
as.factor(region)Kamčatskij kraj	3.699*** (0.999)	2.623* (1.144)	0.358 (1.229)	4.193*** (1.271)
as.factor(region)Karačaevo-Čerkesskaya Respublika	21.617*** (1.463)	29.319*** (1.776)	55.413*** (1.802)	51.014*** (1.848)
as.factor(region)Kemerovskaya oblast - Kuzbass				34.795***

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(region)Kirovskaya oblast	-6.905*** (0.717)	-0.023 (0.866)	-3.847*** (0.885)	3.968*** (0.910)
as.factor(region)Kostromskaya oblast	-6.533*** (0.877)	-1.852 (1.037)	-4.372*** (1.080)	-0.916 (1.115)
as.factor(region)Krasnoyarskij kraj	-6.941*** (0.568)	-4.694*** (0.669)	-8.047*** (0.700)	2.996*** (0.724)
as.factor(region)Krasnodarskij kraj	7.764*** (0.580)	1.471* (0.711)	1.951** (0.722)	20.832*** (0.736)
as.factor(region)Kurganskaya oblast	0.388 (0.872)	9.459*** (0.968)	14.132*** (1.074)	4.046*** (1.040)
as.factor(region)Kurskaya oblast	1.046 (0.675)	3.525*** (0.785)	7.272*** (0.831)	-0.444 (0.860)
as.factor(region)Leningradskaya oblast	-1.541* (0.692)	1.410 (0.816)	-0.628 (0.857)	2.332** (0.878)
as.factor(region)Lipeckaya oblast	-1.210 (4.462)		5.592 (5.484)	25.780*** (5.691)
as.factor(region)Magadanskaya oblast	7.551*** (1.488)	-0.937 (1.714)	2.094 (1.830)	-4.739* (1.900)
as.factor(region)Moskovskaya oblast	-2.866*** (0.503)	-3.427*** (0.600)	-4.109*** (0.622)	7.311*** (0.640)
as.factor(region)Murmanskaya oblast	-2.333** (0.729)	-2.711** (0.867)	-5.394*** (0.897)	-2.090* (0.923)
as.factor(region)Neneckij avtonomnyj okrug	-1.002 (2.673)	4.435 (3.069)	5.211 (3.285)	4.257 (2.940)
as.factor(region)Nižegorodskaya oblast	-2.133*** (7.347***)		-1.223 (7.347***)	4.655*** (7.347***)

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(region)Novgorodskaya oblast	(0.546) −11.797***	(0.668) −1.515	(0.672) −6.897***	(0.694) −0.115
as.factor(region)Novosibirskaya oblast	(0.846) −7.674***	(1.660) 0.084	(1.042) −8.733***	(1.076) −1.348
as.factor(region)Omskaya oblast	(0.664) −6.040***	(0.798) 0.888	(0.819) −5.500***	(0.842) 1.249
as.factor(region)Orenburgskaya oblast	(0.581) −2.338***	(0.676) −3.447***	(0.716) −5.651***	(0.741) 1.966**
as.factor(region)Orlovskaya oblast	(0.591) −1.509	(0.693) 4.713***	(0.729) 2.286*	(0.754) 3.536***
as.factor(region)Penzenskaya oblast	(0.622) 5.821***	(0.718) 4.948***	(0.766) 11.579***	(0.793) 11.043***
as.factor(region)Permskij kraj	(0.634) −3.569***	(0.836) −12.344***	(0.787) −9.778***	(0.804) −1.486
as.factor(region)Primorskij kraj	(0.572) −6.675***	(0.734) 1.157	(0.708) −9.055***	(0.728) 1.440*
as.factor(region)Pskovskaya oblast	(0.781) 0.321	(0.899) 0.183	(0.961) 1.456	(0.997) 5.725***
as.factor(region)Ryazanskaya oblast	(0.727) −3.958***	(0.851) 0.983	(0.896) −1.704	(0.920) 5.742***
as.factor(region)Respublika Adygeya (Adygeya)	(1.482) −2.012	(1.822) 8.249***	(1.833) 3.907*	(1.865) 21.417***
as.factor(region)Respublika Altaj	(2.164) −6.980**	(2.576) 3.912	(2.664) −0.910	(2.744) 4.095
as.factor(region)Respublika Baškortostan	3.189***	9.962***	24.159***	27.179***

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(region)Respublika Buryatiya	(0.903) 9.467***	(1.154) 13.742***	(1.118) −2.812*	(1.128) 5.850***
as.factor(region)Respublika Dagestan	(1.074) 16.489***	(1.335) 30.613***	(1.324) 47.894***	(1.355) 47.728***
as.factor(region)Respublika Hakasiya	(1.056) −3.715***	(1.305) 0.273	(1.299) −5.650***	(1.329) −3.227*
as.factor(region)Respublika Ingus̄etiya	(1.070) as.factor(region)Respublika Kalmykiya	(1.292) 1.834 (1.584)	(1.318) 16.249*** (1.952)	(1.353) 45.916*** (1.949)
as.factor(region)Respublika Kareliya	−7.244*** (1.118)	−4.454** (1.422)	1.029 (1.379)	2.047 (1.407)
as.factor(region)Respublika Komi	−8.699*** (1.057)	8.235*** (1.312)	−2.553 (1.304)	−1.749 (1.329)
as.factor(region)Respublika Krym	9.597*** (1.567)		11.444*** (1.930)	12.768*** (1.999)
as.factor(region)Respublika Marij Él	−3.817*** (1.094)	6.764*** (1.339)	9.030*** (1.349)	4.252** (1.380)
as.factor(region)Respublika Mordoviya	2.350* (1.036)	31.972*** (1.260)	36.888*** (1.279)	19.908*** (1.311)
as.factor(region)Respublika Saha (yakutiya)	2.697** (1.003)	12.373*** (1.219)	0.353 (1.237)	9.841*** (1.268)
as.factor(region)Respublika Severnaya Osetiya - Alaniya	22.799*** (1.049)	21.394*** (1.277)	45.878*** (1.293)	49.612*** (1.323)
as.factor(region)Respublika Tatarstan (Tatarstan)	9.349***	17.859***	34.353***	41.015***

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(region)Respublika Tyva	(0.490) 23.053*** (1.523)	(0.569) 28.940*** (1.794)	(0.604) 44.406*** (1.875)	(0.625) 35.668*** (1.937)
as.factor(region)Rostovskaya oblast	-5.260*** (0.512)	0.587 (0.600)	0.494 (0.631)	2.296*** (0.653)
as.factor(region)Sahalinskaya oblast	-8.315*** (0.871)	-7.363*** (1.033)	-10.023*** (1.072)	-1.353 (1.113)
as.factor(region)Samarskaya oblast	-3.119*** (0.605)	6.806*** (1.935)	3.176*** (0.767)	3.844*** (0.767)
as.factor(region)Saratovskaya oblast	-1.041 (1.326)	5.706*** (1.624)	25.170*** (1.632)	3.820* (1.704)
as.factor(region)Smolenskaya oblast	-5.531*** (0.669)	-4.159*** (0.769)	-5.684*** (0.824)	-0.538 (0.850)
as.factor(region)Stavropol'skij kraj	8.515*** (0.796)	2.456* (0.983)	0.263 (0.983)	31.114*** (1.003)
as.factor(region)Sverdlovskaya oblast	-3.869*** (0.511)	-6.324*** (0.599)	-2.240*** (0.630)	12.007*** (0.651)
as.factor(region)Tambovskaya oblast	1.697* (0.699)	8.092*** (0.804)	-0.817 (0.863)	17.270*** (0.889)
as.factor(region)Tomskaya oblast	-2.003** (0.644)	-1.090 (0.740)	-4.378*** (0.794)	6.586*** (0.823)
as.factor(region)Tulskaya oblast	0.269 (0.647)		-3.082*** (0.797)	11.854*** (0.825)
as.factor(region)Tümenskaya oblast	9.147*** (0.723)	21.657*** (1.650)	34.702*** (0.894)	19.835*** (0.917)
as.factor(region)Tverskaya oblast	-6.121*** (-6.121***)	-2.426*** (-2.426***)	2.378** (2.378**)	2.479** (2.479**)

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(region)Udmurtskaya Respublika	(0.606) −8.215*** (1.752)	(0.701) 0.135 (2.067)	(0.746) 0.075 (2.156)	(0.773) 5.837** (2.224)
as.factor(region)Ulyanovskaya oblast	−10.625*** (0.745)		−5.064*** (0.959)	−5.091*** (0.949)
as.factor(region)Vladimirskaya oblast	−2.147** (0.742)	−9.257*** (0.902)	−5.513*** (0.915)	−1.340 (0.939)
as.factor(region)Volgogradskaya oblast	0.311 (0.601)	−2.195** (0.709)	−2.075** (0.740)	26.219*** (0.765)
as.factor(region)Vologodskaya oblast	0.212 (0.685)	−1.641* (0.809)	−2.778** (0.845)	6.681*** (0.873)
as.factor(region)Voronežskaya oblast	−6.971*** (0.712)	−0.004 (0.886)	−0.129 (0.879)	5.317*** (0.896)
as.factor(region)Zabajkalskij kraj	−10.123*** (0.978)	−2.616* (1.327)	−7.879*** (1.208)	−2.517* (1.238)
as.factor(market)02	−0.892 (0.614)	−0.141 (0.771)	−0.866 (0.756)	−2.263** (0.764)
as.factor(market)03	−1.068 (0.612)	−0.048 (0.761)	−1.734* (0.754)	−2.454** (0.763)
as.factor(market)05	−0.732 (0.830)	1.013 (1.008)	−2.006* (1.022)	−4.243*** (1.041)
as.factor(market)06	−4.677*** (1.062)	−2.133 (1.330)	−3.334* (1.317)	−5.476*** (1.348)
as.factor(market)07	−2.740** (0.919)	−0.097 (1.306)	−2.972** (1.138)	−3.197** (1.149)
as.factor(market)08	−0.217	−0.294	−1.132	−1.378

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(market)09	(0.600) −0.510 (0.651)	(0.766) −1.139 (0.883)	(0.738) −1.558 (0.806)	(0.749) −2.526** (0.813)
as.factor(market)10	−0.809 (0.589)	0.526 (0.751)	−0.704 (0.725)	−1.290 (0.734)
as.factor(market)11	−1.972** (0.600)	−0.034 (0.762)	−2.716*** (0.739)	−3.200*** (0.744)
as.factor(market)12	−1.599 (0.824)	0.778 (1.132)	−1.455 (1.016)	−4.196*** (1.037)
as.factor(market)13	−1.165 (0.614)	0.489 (0.789)	−1.878* (0.756)	−1.200 (0.764)
as.factor(market)14	−0.410 (0.594)	0.865 (0.762)	−1.382 (0.731)	−0.826 (0.740)
as.factor(market)15	−1.065 (0.617)	0.097 (0.790)	−3.534*** (0.764)	−2.812*** (0.773)
as.factor(market)16	−0.314 (0.634)	−0.369 (0.813)	−0.222 (0.781)	−0.620 (0.792)
as.factor(market)17	−0.580 (0.598)	0.483 (0.784)	−2.344** (0.739)	−3.862*** (0.751)
as.factor(market)18	−1.581** (0.594)	0.551 (0.762)	−1.935** (0.733)	−1.754* (0.741)
as.factor(market)19	−1.696* (0.751)	−1.579 (0.965)	−2.849** (0.931)	−4.015*** (0.930)
as.factor(market)20	0.318 (0.599)	0.216 (0.789)	−0.923 (0.739)	−1.221 (0.752)
as.factor(market)21	−0.451	−0.934	−2.892*** (0.739)	−2.619** (0.752)

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(market)22	(0.680) 0.168	(0.873) 0.082	(0.841) −0.215	(0.853) −0.223
as.factor(market)23	(0.649) −1.137	(0.814) 0.051	(0.799) −0.828	(0.806) −2.178**
as.factor(market)24	(0.641) −1.693**	(0.812) −1.327	(0.790) −3.367***	(0.793) −4.215***
as.factor(market)25	(0.640) −1.229	(0.835) −1.223	(0.788) −1.220	(0.804) −2.250**
as.factor(market)26	(0.686) −1.432*	(0.905) 0.728	(0.849) −2.935***	(0.862) −3.486***
as.factor(market)27	(0.637) −1.683**	(0.791) −1.132	(0.729) −2.450**	(0.734) −0.803
as.factor(market)28	(0.646) −0.175	(0.809) 0.275	(0.796) 0.513	(0.806) −0.760
as.factor(market)29	(0.659) −1.641*	(0.903) −0.373	(0.818) −1.259	(0.822) −2.241**
as.factor(market)30	(0.627) −1.696**	(0.833) −0.265	(0.775) −2.482**	(0.782) −3.341***
as.factor(market)31	(0.672) −1.018	(0.844) −0.264	(0.827) −1.159	(0.839) −2.226**
as.factor(market)32	(0.610) −0.780	(0.792) −0.282	(0.753) −2.394**	(0.765) −2.745***
as.factor(market)33	(0.609) −0.571	(0.791) −0.130	(0.749) −0.877	(0.759) −1.357
as.factor(market)35	−2.477***	−0.751	−2.580***	−2.528***

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(market)36	(0.584) −1.004 (0.634)	(0.764) 0.254 (0.798)	(0.719) −1.748* (0.783)	(0.726) −3.608*** (0.777)
as.factor(market)37	−1.247* (0.635)	−1.130 (0.798)	−1.951* (0.785)	−2.534** (0.796)
as.factor(market)38	−0.745 (0.643)	0.997 (0.810)	−1.912* (0.794)	−1.207 (0.802)
as.factor(market)39	−3.320** (1.029)	−1.516 (1.269)	−3.762** (1.266)	−5.982*** (1.303)
as.factor(market)41	−0.844 (0.713)	1.598 (0.873)	−2.239* (0.877)	−0.004 (0.887)
as.factor(market)42	0.086 (0.602)	1.963* (0.836)	−0.710 (0.741)	−0.431 (0.753)
as.factor(market)43	−0.381 (0.691)	−0.729 (0.876)	0.219 (0.853)	−2.320** (0.855)
as.factor(market)45	−1.433* (0.698)	−0.138 (0.920)	−1.252 (0.861)	1.080 (0.870)
as.factor(market)46	0.519 (0.684)	−0.307 (0.866)	−1.369 (0.842)	−0.556 (0.857)
as.factor(market)47	2.168** (0.810)	0.262 (1.003)	0.228 (0.995)	−1.842 (1.014)
as.factor(market)49	0.632 (0.676)	1.564 (0.916)	0.523 (0.830)	0.146 (0.845)
as.factor(market)50	−1.726* (0.802)	−1.734 (1.010)	−2.717** (0.992)	−2.835** (0.988)
as.factor(market)51	−2.857***	0.410	−4.175***	−4.060***

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(market)52	(0.732) −0.654 (0.660)	(0.953) 1.016 (0.860)	(0.915) −1.211 (0.814)	(0.905) −0.805 (0.820)
as.factor(market)53	−0.825 (0.597)	−0.434 (0.786)	−2.949*** (0.739)	−2.281** (0.748)
as.factor(market)55	−0.775 (0.621)	0.374 (0.783)	−1.788* (0.766)	−0.710 (0.776)
as.factor(market)56	−0.841 (0.691)	0.640 (0.848)	0.208 (0.850)	0.191 (0.857)
as.factor(market)58	−0.939 (0.637)	−0.238 (0.789)	−1.413 (0.787)	−1.652* (0.788)
as.factor(market)59	0.427 (0.662)	0.865 (0.835)	−2.058* (0.815)	−0.801 (0.827)
as.factor(market)60	−0.150 (0.599)	0.062 (0.753)	−0.988 (0.738)	−1.667* (0.751)
as.factor(market)61	−1.348* (0.574)	0.043 (0.730)	−1.944** (0.708)	−2.694*** (0.718)
as.factor(market)62	0.116 (0.669)	−1.420 (0.865)	0.629 (0.825)	0.318 (0.828)
as.factor(market)63	−0.519 (0.640)	−0.670 (0.819)	−2.355** (0.790)	−3.195*** (0.797)
as.factor(market)64	0.430 (0.606)	1.530 (0.787)	0.711 (0.750)	−1.577* (0.754)
as.factor(market)65	−2.209** (0.761)	−0.578 (1.155)	−3.222*** (0.940)	−3.319*** (0.962)
as.factor(market)66	−0.575	−0.259	−0.845	−1.441

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(market)68	(0.640) −0.470	(0.832) 1.400	(0.794) −1.682	(0.800) −0.361
as.factor(market)69	(0.712) −0.832	(0.951) 0.820	(0.875) −0.526	(0.884) −0.815
as.factor(market)70	(0.726) −1.817** (0.640)	(0.958) 0.149 (0.819)	(0.895) −0.757 (0.787)	(0.909) −1.564 (0.800)
as.factor(market)71	(0.641) −1.926** (0.641)	(0.837) −0.142 (0.837)	(0.789) −1.146 (0.789)	(0.802) −2.513** (0.802)
as.factor(market)72	(0.679) −0.560	(0.886) −0.182	(0.837) −0.152	(0.849) −1.603
as.factor(market)73	(0.694) −0.510	(0.871) 1.095	(0.858) −1.382	(0.871) −0.481
as.factor(market)74	(0.677) −0.055	(0.849) 1.559	(0.835) −1.094	(0.842) −0.506
as.factor(market)75	(0.621) −1.057	(0.787) 0.968	(0.769) −2.115**	(0.776) −1.414
as.factor(market)77	(0.675) −0.861	(0.921) 0.194	(0.832) 0.022	(0.838) −1.716*
as.factor(market)78	(0.706) −0.131	(0.898) 0.136	(0.870) −1.844*	(0.880) −1.429
as.factor(market)79	(0.711) 1.846**	(0.890) 3.250***	(0.880) 0.786	(0.882) 1.534
as.factor(market)80	(0.657) −2.411***	(0.838) 0.326	(0.810) −2.491**	(0.818) −1.998*
as.factor(market)81	−0.271	1.445	−0.055	−1.127

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(market)82	(0.634) −0.337	(0.790) 0.186	(0.781) −0.871	(0.780) −0.752
as.factor(market)84	(0.642) −2.087***	(0.867) −1.200	(0.794) −3.199***	(0.802) −5.413***
as.factor(market)85	(0.623) −0.300	(0.806) −0.838	(0.775) −1.090	(0.774) 1.140
as.factor(market)86	(0.638) −1.205	(0.788) −0.044	(0.786) 0.626	(0.794) −0.394
as.factor(market)87	(0.638) −1.958**	(0.786) −0.540	(0.785) −4.731***	(0.796) −5.834***
as.factor(market)88	(0.663) −0.663	(0.841) 0.007	(0.818) −3.168***	(0.829) −3.330***
as.factor(market)90	(0.673) −0.208	(0.839) 0.305	(0.833) −1.308	(0.841) −2.118*
as.factor(market)91	(0.754) −2.181**	(0.960) 0.157	(0.933) −3.627***	(0.926) −4.398***
as.factor(market)92	(0.702) −1.027	(0.936) −2.075*	(0.865) −4.213***	(0.886) −5.870***
as.factor(market)93	(0.678) 0.122	(0.841) 0.123	(0.835) −0.098	(0.853) −1.236
as.factor(market)94	(0.857) 0.011	(1.139) −1.401	(1.056) −1.526	(1.060) −2.917**
as.factor(market)95	(0.617) −0.502	(0.781) 1.182	(0.759) −0.289	(0.770) −0.913
as.factor(market)96	(−0.270) −0.270	(−0.073) −2.034**	(−0.759) −2.034**	(−0.937)* −1.937*

Table 2: (continued)

	<i>Dependent variable:</i>			
	Model 5 (1)	Model 6 (2)	Model 7 (3)	Model 8 (4)
as.factor(market)97	(0.635) -3.353** (1.026)	(0.815) -4.706*** (1.276)	(0.783) -9.417*** (1.265)	(0.795) -6.926*** (1.311)
as.factor(market)98	-5.192 (9.578)	18.242 (11.332)	-0.703 (11.771)	0.626 (11.999)
as.factor(market)99	-0.632 (1.763)	6.341** (2.055)	-1.454 (2.166)	-4.185 (2.244)
uik_population	-0.001*** (0.00005)	-0.0004*** (0.0001)	-0.001*** (0.0001)	-0.002*** (0.0001)
Observations	31,999	24,539	31,439	33,564
R <sup>2</sup>	0.375	0.390	0.592	0.579
Adjusted R <sup>2</sup>	0.264	0.272	0.522	0.509

*Note:* \*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Table 3: Regression results (regional + sectoral fixed effects): vote share - Parliament

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
proximity	-0.561*** (0.073)	-0.315*** (0.047)	0.681*** (0.072)	0.117 (0.082)
as.factor(region)Yamalo-Neneckij avtonomnyj okrug	-4.884***	5.860***	-9.978***	-26.501***

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(region)Amurskaya oblast	(0.452) 8.436***	(0.301) 4.528***	(0.450) 0.918	(0.575) -3.733***
as.factor(region)Arhangelskaya oblast	(0.491) -1.372**	(0.325) 3.209***	(0.488) -3.271***	(0.595) -14.239***
as.factor(region)Yaroslavskaya oblast	(0.451) -0.440	(0.297) (0.244)	(0.449) (0.461)	(0.555) -8.049***
as.factor(region)Astrahanskaya oblast	-7.334*** (0.552)	-2.555*** (0.367)	-0.892 (0.549)	-14.482*** (0.684)
as.factor(region)Belgorodskaya oblast	-5.554*** (0.425)	-1.330*** (0.281)	1.647*** (0.423)	-10.899*** (0.520)
as.factor(region)Bryanskaya oblast	-10.013*** (0.434)	0.145 (0.287)	-1.022* (0.431)	-17.678*** (0.529)
as.factor(region)Čečenskaya Respublika	-22.224*** (0.615)	-9.442*** (0.399)	-17.525*** (0.611)	-33.466*** (0.739)
as.factor(region)Čelyabinskaya oblast	-3.262*** (0.261)	-0.774*** (0.174)	-4.005*** (0.260)	-13.710*** (0.329)
as.factor(region)Čukotskij avtonomnyj okrug	3.496* (1.581)	11.601*** (1.060)	-5.964*** (1.573)	-17.223*** (1.676)
as.factor(region)Čuvaškaya Respublika - Čuvašiya	-6.731*** (0.448)	-1.587*** (0.296)	-1.337** (0.446)	-9.167*** (0.550)
as.factor(region)Evrejskaya avtonomnaya oblast	4.682*** (0.875)	2.373*** (0.586)	2.870*** (0.870)	-8.930*** (1.000)
as.factor(region)gorod Moskva	-7.992*** (0.296)	-1.867*** (0.196)	-2.459*** (0.295)	-4.208*** (0.366)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(region)gorod Sankt-Peterburg	-11.015*** (0.307)	-2.924*** (0.203)	-4.606*** (0.305)	-16.123*** (0.383)
as.factor(region)gorod Sevastopol	-6.526*** (0.651)	-0.292 (0.435)	-4.295*** (0.647)	-21.121*** (0.844)
as.factor(region)Habarovskij kraj	2.971*** (0.452)	6.507*** (0.298)	1.719*** (0.449)	-4.742*** (0.556)
as.factor(region)Irkutskaya oblast	-3.533*** (0.357)	-0.779*** (0.236)	8.299*** (0.355)	-5.472*** (0.443)
as.factor(region)Ivanovskaya oblast	-3.184*** (0.407)	-0.153 (0.269)	3.750*** (0.405)	-3.074*** (0.494)
as.factor(region)Kabardino-Balkarskaya Respublika	-22.695*** (0.671)	-9.456*** (0.441)	0.941 (0.667)	-16.912*** (0.826)
as.factor(region)Kaliningradskaya oblast	-4.137*** (0.422)	0.662* (0.279)	-0.290 (0.420)	-10.295*** (0.514)
as.factor(region)Kalužskaya oblast	-4.697*** (0.458)	-0.241 (0.302)	0.669 (0.456)	-10.712*** (0.562)
as.factor(region)Kamčatskij kraj	1.037 (0.530)	3.940*** (0.354)	-3.111*** (0.528)	-6.801*** (0.686)
as.factor(region)Karačaevo-Čerkesskaya Respublika	-21.524*** (0.778)	-7.463*** (0.514)	-8.521*** (0.774)	-20.344*** (0.969)
as.factor(region)Kemerovskaya oblast - Kuzbass		-2.581*** (0.223)		-23.838*** (0.416)
as.factor(region)Kirovskaya oblast	3.781*** (0.382)	3.145*** (0.253)	-3.353*** (0.380)	-14.567*** (0.470)
as.factor(region)Kostromskaya oblast	-3.070*** (0.466)	-0.018 (0.310)	5.421*** (0.464)	-3.006*** (0.564)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(region)Krasnoyarskij kraj	-0.996*** (0.302)	5.130*** (0.201)	-2.595*** (0.300)	-10.945*** (0.376)
as.factor(region)Krasnodarskij kraj	-6.316*** (0.312)	-2.392*** (0.205)	-1.133*** (0.310)	-13.894*** (0.387)
as.factor(region)Kurganskaya oblast	-5.784*** (0.463)	1.574*** (0.289)	-1.316** (0.461)	-9.409*** (0.529)
as.factor(region)Kurskaya oblast	-6.421*** (0.359)	2.233*** (0.239)	-4.150*** (0.357)	-9.899*** (0.444)
as.factor(region)Leningradskaya oblast	-7.154*** (0.370)	0.079 (0.244)	-5.972*** (0.368)	-12.258*** (0.451)
as.factor(region)Lipeckaya oblast	-6.043* (2.366)	-1.615 (1.584)	0.189 (2.355)	-13.110*** (2.538)
as.factor(region)Magadanskaya oblast	-3.466*** (0.789)	2.041*** (0.529)	1.618* (0.786)	-5.332*** (0.965)
as.factor(region)Moskovskaya oblast	-6.147*** (0.269)	-0.992*** (0.178)	-0.780** (0.267)	-11.107*** (0.334)
as.factor(region)Murmanskaya oblast	-1.242** (0.387)	2.801*** (0.257)	-4.760*** (0.385)	-12.703*** (0.486)
as.factor(region)Neneckij avtonomnyj okrug	0.727 (1.418)	0.505 (0.818)	6.540*** (1.411)	2.949* (1.398)
as.factor(region)Nižegorodskaya oblast	-7.383*** (0.290)	-1.232*** (0.193)	-1.990*** (0.289)	-11.737*** (0.359)
as.factor(region)Novgorodskaya oblast	-6.763*** (0.449)	-0.874** (0.299)	0.596 (0.447)	-10.565*** (0.546)
as.factor(region)Novosibirskaya oblast	-2.117*** (0.353)	0.637** (0.234)	5.557*** (0.351)	-5.452*** (0.439)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(region)Omskaya oblast	-5.433*** (0.309)	-2.145*** (0.206)	12.026*** (0.307)	2.430*** (0.396)
as.factor(region)Orenburgskaya oblast	2.265*** (0.314)	1.079*** (0.210)	2.305*** (0.313)	-5.694*** (0.398)
as.factor(region)Orlovskaya oblast	-3.346*** (0.440)	-0.572 (0.292)	2.988*** (0.438)	-8.445*** (0.537)
as.factor(region)Penzenskaya oblast	-8.138*** (0.331)	0.618** (0.221)	-1.006** (0.329)	-12.891*** (0.412)
as.factor(region)Permskij kraj	-5.207*** (0.340)	1.810*** (0.224)	-1.848*** (0.338)	-9.726*** (0.419)
as.factor(region)Primorskij kraj	-1.308*** (0.306)	-0.942*** (0.203)	3.683*** (0.304)	-1.361*** (0.381)
as.factor(region)Pskovskaya oblast	-7.729*** (0.415)	-0.749** (0.277)	1.437*** (0.413)	-10.393*** (0.480)
as.factor(region)Ryazanskaya oblast	-5.665*** (0.387)	0.723** (0.256)	0.006 (0.385)	-11.595*** (0.472)
as.factor(region)Respublika Adygeya (Adygeya)	-5.076*** (0.791)	-3.638*** (0.519)	-1.352 (0.787)	-14.733*** (0.954)
as.factor(region)Respublika Altaj	-4.861*** (1.149)	0.823 (0.763)	4.056*** (1.144)	-1.446 (1.427)
as.factor(region)Respublika Baškortostan	-13.731*** (0.482)	-0.085 (0.314)	4.572*** (0.480)	-17.020*** (0.586)
as.factor(region)Respublika Buryatiya	-8.745*** (0.571)	-4.578*** (0.377)	6.087*** (0.568)	-5.816*** (0.714)
as.factor(region)Respublika Dagestan	-22.145*** (0.561)	-5.146*** (0.370)	-13.622*** (0.558)	-28.039*** (0.693)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(region)Respublika Hakasiya	-1.775** (0.569)	-2.136*** (0.376)	3.953*** (0.566)	-1.608* (0.706)
as.factor(region)Respublika Ingušetiya		-7.783*** (0.542)		-29.503*** (1.041)
as.factor(region)Respublika Kalmykiya	-17.833*** (0.842)	-6.457*** (0.557)	-4.697*** (0.838)	-3.597*** (1.017)
as.factor(region)Respublika Kareliya	-4.896*** (0.595)	-0.697 (0.392)	-3.991*** (0.592)	-17.214*** (0.717)
as.factor(region)Respublika Komi	1.248* (0.563)	1.580*** (0.370)	-4.936*** (0.560)	-5.259*** (0.681)
as.factor(region)Respublika Krym	-11.169*** (0.833)	-2.848*** (0.556)	-11.178*** (0.829)	-26.169*** (1.010)
as.factor(region)Respublika Marij Él	-9.964*** (0.582)	-1.344*** (0.384)	10.173*** (0.579)	3.671*** (0.718)
as.factor(region)Respublika Mordoviya	-13.463*** (0.552)	0.673 (0.365)	-11.369*** (0.549)	-18.341*** (0.650)
as.factor(region)Respublika Saha (yakutiya)	-6.979*** (0.534)	-4.035*** (0.353)	-4.320*** (0.531)	2.653*** (0.647)
as.factor(region)Respublika Severnaya Osetiya - Alaniya	-21.070*** (0.558)	-8.319*** (0.368)	4.816*** (0.555)	-21.958*** (0.683)
as.factor(region)Respublika Tatarstan (Tatarstan)	-17.961*** (0.261)	-4.938*** (0.174)	-11.712*** (0.259)	-23.289*** (0.331)
as.factor(region)Respublika Tyva	-17.336*** (0.809)	-6.326*** (0.539)	-11.342*** (0.805)	-26.920*** (0.966)
as.factor(region)Rostovskaya oblast	-6.521*** (0.272)	-1.411*** (0.182)	-0.431 (0.271)	-6.893*** (0.344)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(region)Sahalinskaya oblast	-0.422 (0.462)	-0.047 (0.310)	0.808 (0.460)	-1.349* (0.579)
as.factor(region)Samarskaya oblast	-5.410*** (0.331)	-0.269 (0.214)	1.117*** (0.329)	-5.531*** (0.404)
as.factor(region)Saratovskaya oblast	-12.057*** (0.704)	-3.616*** (0.474)	-5.716*** (0.701)	-7.350*** (0.898)
as.factor(region)Smolenskaya oblast	-0.618 (0.356)	2.461*** (0.237)	0.666 (0.354)	-8.290*** (0.432)
as.factor(region)Stavropol'skij kraj	-5.125*** (0.424)	-4.307*** (0.279)	-3.455*** (0.422)	-18.857*** (0.520)
as.factor(region)Sverdlovskaya oblast	-3.867*** (0.272)	-0.020 (0.181)	-3.839*** (0.270)	-12.214*** (0.341)
as.factor(region)Tambovskaya oblast	-12.175*** (0.372)	-3.781*** (0.247)	-4.974*** (0.370)	-17.882*** (0.458)
as.factor(region)Tomskaya oblast	-1.084** (0.343)	2.501*** (0.229)	-5.124*** (0.341)	-10.369*** (0.443)
as.factor(region)Tulskaya oblast	-5.741*** (0.344)	-1.474*** (0.229)	0.148 (0.342)	-15.219*** (0.427)
as.factor(region)Tûmenskaya oblast	-3.378*** (0.386)	4.509*** (0.255)	-2.515*** (0.384)	-19.263*** (0.481)
as.factor(region)Tverskaya oblast	-5.233*** (0.322)	0.850*** (0.215)	-2.411*** (0.320)	-9.108*** (0.384)
as.factor(region)Udmurtskaya Respublika	-6.612*** (0.930)	-0.522 (0.619)	-2.120* (0.926)	-5.181*** (1.110)
as.factor(region)Ulyanovskaya oblast	-3.722*** (0.414)	-0.300 (0.264)	7.905*** (0.412)	6.023*** (0.492)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(region)Vladimirskaya oblast	-3.525*** (0.395)	-0.263 (0.261)	-3.773*** (0.393)	-6.486*** (0.485)
as.factor(region)Volgogradskaya oblast	-4.911*** (0.319)	2.512*** (0.213)	-0.920** (0.318)	-18.147*** (0.402)
as.factor(region)Vologodskaya oblast	0.544 (0.365)	3.022*** (0.243)	-3.487*** (0.363)	-11.127*** (0.447)
as.factor(region)Voronežskaya oblast	-10.514*** (0.379)	-2.509*** (0.249)	4.987*** (0.378)	-7.356*** (0.466)
as.factor(region)Zabajkalskij kraj	7.917*** (0.521)	1.723*** (0.345)	1.418** (0.519)	-10.400*** (0.647)
as.factor(market)02	0.041 (0.326)	0.314 (0.213)	0.420 (0.325)	0.340 (0.383)
as.factor(market)03	-1.183*** (0.325)	-0.364 (0.212)	0.205 (0.324)	0.056 (0.386)
as.factor(market)05	-2.666*** (0.441)	-0.628* (0.290)	-0.119 (0.439)	0.925 (0.550)
as.factor(market)06	-1.425* (0.568)	0.014 (0.375)	0.599 (0.566)	-0.281 (0.711)
as.factor(market)07	0.194 (0.491)	0.056 (0.320)	-0.748 (0.489)	0.337 (0.564)
as.factor(market)08	-0.264 (0.319)	-0.115 (0.208)	0.128 (0.317)	-0.338 (0.378)
as.factor(market)09	-1.258*** (0.348)	-0.165 (0.226)	-0.543 (0.346)	-0.397 (0.420)
as.factor(market)10	-0.869** (0.313)	-0.311 (0.204)	0.051 (0.311)	-0.149 (0.368)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(market)11	-0.252 (0.319)	0.185 (0.207)	0.135 (0.317)	-0.026 (0.378)
as.factor(market)12	-1.082* (0.439)	-0.222 (0.289)	-0.510 (0.436)	0.157 (0.546)
as.factor(market)13	-0.787* (0.326)	-0.428* (0.212)	-0.365 (0.325)	-0.534 (0.391)
as.factor(market)14	-1.004** (0.316)	-0.453* (0.206)	-0.501 (0.314)	-0.269 (0.378)
as.factor(market)15	-0.057 (0.330)	-0.119 (0.215)	-1.073** (0.328)	-0.847* (0.393)
as.factor(market)16	-0.311 (0.337)	-0.183 (0.220)	-0.828* (0.335)	-0.640 (0.395)
as.factor(market)17	-1.389*** (0.319)	-0.168 (0.209)	-0.257 (0.317)	-0.024 (0.386)
as.factor(market)18	-0.790* (0.316)	-0.221 (0.206)	-0.100 (0.315)	-0.163 (0.380)
as.factor(market)19	-0.838* (0.402)	-0.246 (0.259)	1.080** (0.400)	0.527 (0.482)
as.factor(market)20	-1.217*** (0.319)	-0.072 (0.209)	-0.072 (0.317)	-0.175 (0.383)
as.factor(market)21	-0.575 (0.363)	1.397*** (0.237)	-0.174 (0.361)	0.528 (0.438)
as.factor(market)22	-1.010** (0.345)	-0.209 (0.224)	0.020 (0.343)	-0.195 (0.410)
as.factor(market)23	-0.657 (0.341)	0.065 (0.221)	-0.238 (0.339)	-0.062 (0.400)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(market)24	-1.247*** (0.340)	0.047 (0.224)	-0.177 (0.339)	0.075 (0.413)
as.factor(market)25	-0.095 (0.366)	0.102 (0.240)	-0.504 (0.364)	0.338 (0.435)
as.factor(market)26	-1.450*** (0.315)	-0.360 (0.204)	0.289 (0.313)	0.371 (0.379)
as.factor(market)27	-1.183*** (0.339)	-0.408 (0.221)	0.676* (0.338)	-0.163 (0.403)
as.factor(market)28	-0.180 (0.344)	-0.198 (0.224)	-0.764* (0.342)	-0.018 (0.410)
as.factor(market)29	-0.952** (0.353)	-0.373 (0.229)	-0.178 (0.351)	-0.403 (0.425)
as.factor(market)30	-1.127*** (0.335)	-0.211 (0.218)	0.288 (0.333)	0.519 (0.400)
as.factor(market)31	-0.555 (0.357)	-0.356 (0.233)	-0.722* (0.355)	0.126 (0.429)
as.factor(market)32	-0.502 (0.325)	-0.027 (0.213)	0.493 (0.323)	0.180 (0.392)
as.factor(market)33	-0.415 (0.323)	-0.111 (0.211)	-0.566 (0.322)	0.325 (0.388)
as.factor(market)35	-0.206 (0.310)	0.064 (0.202)	0.150 (0.309)	-0.442 (0.364)
as.factor(market)36	-0.777* (0.338)	0.339 (0.216)	-0.477 (0.336)	0.398 (0.391)
as.factor(market)37	-1.110** (0.339)	-0.333 (0.221)	0.388 (0.337)	0.399 (0.406)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(market)38	0.257 (0.342)	0.298 (0.223)	-0.260 (0.341)	-0.394 (0.404)
as.factor(market)39	-2.611*** (0.546)	0.416 (0.363)	-0.758 (0.543)	-0.440 (0.687)
as.factor(market)41	-0.672 (0.378)	-0.738** (0.247)	-1.500*** (0.376)	-0.556 (0.452)
as.factor(market)42	-0.024 (0.320)	-0.316 (0.210)	-0.465 (0.318)	0.054 (0.382)
as.factor(market)43	-1.251*** (0.368)	-0.520* (0.238)	-0.456 (0.366)	0.565 (0.437)
as.factor(market)45	0.651 (0.372)	0.111 (0.242)	-1.068** (0.370)	-0.301 (0.443)
as.factor(market)46	-1.244*** (0.363)	-0.133 (0.239)	-0.038 (0.361)	-0.256 (0.445)
as.factor(market)47	-1.104* (0.429)	-0.346 (0.282)	0.146 (0.427)	-0.223 (0.514)
as.factor(market)49	-1.613*** (0.358)	-0.580* (0.235)	-0.291 (0.357)	-0.687 (0.434)
as.factor(market)50	-0.762 (0.428)	-0.795** (0.275)	0.630 (0.426)	0.206 (0.507)
as.factor(market)51	-2.181*** (0.395)	-0.799** (0.252)	0.170 (0.393)	0.882 (0.470)
as.factor(market)52	-0.456 (0.351)	-0.244 (0.228)	-0.369 (0.349)	0.157 (0.418)
as.factor(market)53	-1.021** (0.319)	0.106 (0.208)	-0.511 (0.317)	0.004 (0.385)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(market)55	-0.193 (0.331)	0.218 (0.216)	-0.072 (0.329)	0.011 (0.394)
as.factor(market)56	0.003 (0.367)	-0.144 (0.239)	-0.626 (0.365)	0.217 (0.437)
as.factor(market)58	-0.669* (0.339)	-0.165 (0.219)	-0.503 (0.338)	-0.151 (0.405)
as.factor(market)59	-1.295*** (0.352)	-0.458* (0.230)	0.041 (0.350)	-0.012 (0.428)
as.factor(market)60	-0.494 (0.318)	-0.060 (0.209)	0.282 (0.317)	-0.255 (0.383)
as.factor(market)61	-0.841** (0.305)	-0.354 (0.200)	-0.227 (0.304)	0.042 (0.366)
as.factor(market)62	-0.998** (0.356)	-0.567* (0.230)	-0.430 (0.354)	0.134 (0.423)
as.factor(market)63	-0.355 (0.341)	0.148 (0.222)	0.301 (0.339)	1.445*** (0.409)
as.factor(market)64	-1.942*** (0.324)	-0.329 (0.210)	-0.194 (0.322)	-0.007 (0.383)
as.factor(market)65	-1.456*** (0.406)	-0.136 (0.268)	0.006 (0.404)	0.470 (0.498)
as.factor(market)66	-1.299*** (0.342)	-0.754*** (0.223)	-0.104 (0.341)	-0.319 (0.413)
as.factor(market)68	0.351 (0.378)	-0.326 (0.246)	-0.220 (0.376)	-0.534 (0.452)
as.factor(market)69	0.335 (0.386)	0.013 (0.253)	-0.483 (0.384)	-0.054 (0.464)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(market)70	-1.068** (0.340)	-0.051 (0.223)	0.358 (0.338)	0.029 (0.410)
as.factor(market)71	0.647 (0.340)	0.152 (0.223)	-0.328 (0.339)	1.147** (0.410)
as.factor(market)72	-1.951*** (0.361)	-0.548* (0.236)	-0.356 (0.359)	-0.549 (0.437)
as.factor(market)73	-0.505 (0.370)	-0.041 (0.243)	0.582 (0.368)	0.758 (0.443)
as.factor(market)74	-0.911* (0.360)	-0.219 (0.234)	-0.475 (0.358)	-0.163 (0.429)
as.factor(market)75	-0.965** (0.332)	-0.187 (0.216)	0.135 (0.330)	0.314 (0.395)
as.factor(market)77	0.056 (0.359)	-0.123 (0.233)	0.215 (0.357)	0.218 (0.425)
as.factor(market)78	-1.048** (0.375)	-0.565* (0.245)	0.401 (0.374)	-0.446 (0.455)
as.factor(market)79	-0.169 (0.380)	-0.362 (0.245)	-0.229 (0.378)	-0.621 (0.456)
as.factor(market)80	-0.286 (0.350)	-0.212 (0.228)	0.583 (0.348)	0.114 (0.413)
as.factor(market)81	-0.563 (0.337)	-0.340 (0.217)	-0.237 (0.335)	-0.031 (0.399)
as.factor(market)82	0.754* (0.343)	0.495* (0.223)	-0.727* (0.341)	-0.270 (0.409)
as.factor(market)84	-1.660*** (0.335)	-0.355 (0.215)	0.366 (0.333)	1.057** (0.398)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(market)85	-0.056 (0.339)	0.120 (0.221)	0.289 (0.338)	-0.601 (0.403)
as.factor(market)86	0.145 (0.339)	0.500* (0.222)	-0.291 (0.337)	0.213 (0.403)
as.factor(market)87	-0.819* (0.359)	-0.278 (0.235)	-0.154 (0.357)	0.124 (0.438)
as.factor(market)88	-1.301*** (0.353)	-0.603** (0.231)	-0.021 (0.351)	-0.568 (0.427)
as.factor(market)90	-1.548*** (0.359)	-0.407 (0.234)	-0.085 (0.358)	0.361 (0.430)
as.factor(market)91	-1.756*** (0.402)	-0.130 (0.258)	0.352 (0.400)	1.061* (0.483)
as.factor(market)92	-3.135*** (0.373)	-1.143*** (0.247)	1.459*** (0.371)	0.237 (0.464)
as.factor(market)93	-0.440 (0.360)	0.158 (0.237)	0.420 (0.359)	-0.002 (0.442)
as.factor(market)94	-2.594*** (0.456)	-0.497 (0.295)	0.170 (0.453)	0.018 (0.557)
as.factor(market)95	-0.417 (0.328)	-0.074 (0.214)	-0.812* (0.326)	-0.092 (0.394)
as.factor(market)96	0.612 (0.338)	0.041 (0.221)	0.234 (0.336)	-0.309 (0.404)
as.factor(market)97	-2.505*** (0.546)	-0.823* (0.365)	0.680 (0.543)	0.920 (0.695)
as.factor(market)98	3.552 (5.079)	-1.596 (3.339)	0.467 (5.054)	-5.549 (6.539)

Table 3: (continued)

	<i>Dependent variable:</i>			
	LDPR 2016 (1)	LDPR 2021 (2)	KPRF 2016 (3)	KPRF 2021 (4)
as.factor(market)99	-6.631*** (0.935)	-3.222*** (0.624)	0.230 (0.930)	-0.747 (1.211)
uik_population	-0.0003*** (0.00003)	-0.0002*** (0.00002)	0.0001*** (0.00003)	
Observations	31,439	33,564	31,439	36,425
R <sup>2</sup>	0.568	0.430	0.514	0.558
Adjusted R <sup>2</sup>	0.493	0.334	0.431	0.490
<i>Note:</i>			*p<0.05; **p<0.01; ***p<0.001	

Table 4: Regression results (regional + sectoral fixed effects): vote share - Parliament

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
proximity	-0.719*** (0.143)	-0.097 (0.158)	0.287*** (0.034)	-0.290** (0.089)
as.factor(region)Yamalo-Neneckij avtonomnyj okrug	30.729*** (0.891)	37.001*** (1.013)	-1.336*** (0.211)	-26.295*** (0.572)
as.factor(region)Amurskaya oblast	1.940* (0.968)	0.883 (1.092)	-1.474*** (0.229)	-3.481*** (0.617)
as.factor(region)Arhangelskaya oblast	10.456*** (0.890)	1.595 (0.996)	-0.532* (0.210)	-13.765*** (0.563)

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(region)Yaroslavskaya oblast		-4.031*** (0.821)		-7.619*** (0.464)
as.factor(region)Astrahanskaya oblast	3.638*** (1.090)	12.208*** (1.232)	-1.072*** (0.258)	-14.728*** (0.696)
as.factor(region)Belgorodskaya oblast	10.635*** (0.839)	11.442*** (0.943)	-1.675*** (0.198)	-10.164*** (0.532)
as.factor(region)Bryanskaya oblast	26.511*** (0.855)	30.583*** (0.965)	-1.890*** (0.202)	-17.463*** (0.545)
as.factor(region)Čečenskaya Respublika	67.782*** (1.213)	69.382*** (1.341)	-3.563*** (0.287)	-33.743*** (0.757)
as.factor(region)Čelyabinskaya oblast	1.634** (0.515)	3.110*** (0.585)	0.253* (0.122)	-13.514*** (0.331)
as.factor(region)Čukotskij avtonomnyj okrug	16.207*** (3.120)	3.298 (3.562)	-2.075** (0.738)	-14.114*** (2.012)
as.factor(region)Čuvašskaya Respublika - Čuvašiya	9.120*** (0.884)	1.736 (0.993)	-0.881*** (0.209)	-8.737*** (0.561)
as.factor(region)Evrejskaya avtonomnaya oblast	4.519** (1.726)	14.427*** (1.969)	-1.982*** (0.408)	-8.004*** (1.112)
as.factor(region)gorod Moskva	4.636*** (0.584)	1.758** (0.658)	7.560*** (0.138)	-4.488*** (0.372)
as.factor(region)gorod Sankt-Peterburg	5.649*** (0.605)	5.826*** (0.683)	8.392*** (0.143)	-16.299*** (0.386)
as.factor(region)gorod Sevastopol	22.071*** (1.284)	27.728*** (1.461)	-2.013*** (0.304)	-21.239*** (0.825)
as.factor(region)Habarovskij kraj	4.981***	-6.146***	-1.183***	-4.129***

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(region)Irkutskaya oblast	(0.891) 4.275*** (0.705)	(1.001) 5.829*** (0.794)	(0.211) −1.087*** (0.167)	(0.566) −5.217*** (0.448)
as.factor(region)Ivanovskaya oblast	4.000*** (0.803)	3.348*** (0.904)	−0.651*** (0.190)	−1.936*** (0.511)
as.factor(region)Kabardino-Balkarskaya Respublika	48.697*** (1.323)	50.761*** (1.480)	−3.491*** (0.313)	−16.779*** (0.836)
as.factor(region)Kalininogradskaya oblast	6.486*** (0.832)	6.371*** (0.936)	0.132 (0.197)	−9.486*** (0.529)
as.factor(region)Kalužskaya oblast	9.420*** (0.904)	5.792*** (1.016)	0.380 (0.214)	−10.522*** (0.574)
as.factor(region)Kamčatskij kraj	13.466*** (1.046)	3.139** (1.188)	−1.467*** (0.247)	−6.891*** (0.671)
as.factor(region)Karačaevо-Čerkesskaya Respublika	50.333*** (1.534)	49.901*** (1.727)	−3.647*** (0.363)	−20.169*** (0.976)
as.factor(region)Kemerovskaya oblast - Kuzbass		41.325*** (0.748)		−23.529*** (0.422)
as.factor(region)Kirovskaya oblast	3.440*** (0.754)	−1.074 (0.851)	−0.465** (0.178)	−14.111*** (0.481)
as.factor(region)Kostromskaya oblast	2.043* (0.919)	−0.803 (1.042)	−0.775*** (0.217)	−2.985*** (0.589)
as.factor(region)Krasnoyarskij kraj	5.923*** (0.596)	5.615*** (0.677)	−0.819*** (0.141)	−11.118*** (0.382)
as.factor(region)Krasnodarskij kraj	19.757*** (0.615)	23.526*** (0.688)	−0.634*** (0.145)	−13.566*** (0.389)
as.factor(region)Kurganskaya oblast	16.244***	3.896***	−1.645***	−9.135***

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(region)Kurskaya oblast	(0.914) 19.562*** (0.707)	(0.972) 6.667*** (0.804)	(0.216) −1.387*** (0.167)	(0.549) −9.366*** (0.454)
as.factor(region)Leningradskaya oblast	12.691*** (0.729)	7.709*** (0.821)	0.355* (0.172)	−12.158*** (0.464)
as.factor(region)Lipeckaya oblast	17.914*** (4.669)	25.342*** (5.321)	−1.557 (1.104)	−11.357*** (3.006)
as.factor(region)Magadanskaya oblast	8.909*** (1.558)	4.770** (1.776)	−1.790*** (0.368)	−3.967*** (1.003)
as.factor(region)Moskovskaya oblast	12.326*** (0.530)	13.814*** (0.598)	1.535*** (0.125)	−10.998*** (0.338)
as.factor(region)Murmanskaya oblast	9.121*** (0.764)	1.657 (0.863)	−0.524** (0.181)	−12.128*** (0.488)
as.factor(region)Neneckij avtonomnyj okrug	1.750 (2.797)	−5.416* (2.749)	−1.833** (0.661)	4.199** (1.553)
as.factor(region)Nižegorodskaya oblast	18.826*** (0.572)	14.011*** (0.649)	−0.799*** (0.135)	−10.615*** (0.367)
as.factor(region)Novgorodskaya oblast	2.840** (0.887)	−0.029 (1.006)	1.441*** (0.210)	−9.589*** (0.568)
as.factor(region)Novosibirskaya oblast	1.486* (0.697)	1.962* (0.787)	0.362* (0.165)	−5.208*** (0.444)
as.factor(region)Omskaya oblast	−2.898*** (0.609)	−1.578* (0.692)	0.050 (0.144)	2.521*** (0.391)
as.factor(region)Orenburgskaya oblast	3.425*** (0.620)	4.334*** (0.705)	−0.324* (0.147)	−5.448*** (0.398)
as.factor(region)Orlovskaya oblast	6.118***	0.311	−1.359***	−7.848***

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(region)Penzenskaya oblast	(0.868) 19.243*** (0.652)	(0.982) 13.156*** (0.742)	(0.205) −0.872*** (0.154)	(0.555) −11.519*** (0.419)
as.factor(region)Permskij kraj	8.356*** (0.670)	3.997*** (0.751)	1.806*** (0.158)	−9.811*** (0.424)
as.factor(region)Primorskij kraj	1.249* (0.603)	2.158** (0.681)	0.105 (0.143)	−0.672 (0.385)
as.factor(region)Pskovskaya oblast	8.749*** (0.818)	5.272*** (0.932)	2.808*** (0.193)	−9.647*** (0.526)
as.factor(region)Ryazanskaya oblast	14.420*** (0.763)	11.085*** (0.860)	−0.416* (0.180)	−10.344*** (0.486)
as.factor(region)Respublika Adygaea (Adygaea)	17.496*** (1.560)	29.025*** (1.743)	−1.656*** (0.369)	−13.975*** (0.985)
as.factor(region)Respublika Altaj	11.810*** (2.268)	3.745 (2.565)	−2.586*** (0.536)	−1.469 (1.449)
as.factor(region)Respublika Baškortostan	23.035*** (0.952)	31.215*** (1.055)	−2.283*** (0.225)	−17.306*** (0.596)
as.factor(region)Respublika Buryatiya	5.526*** (1.127)	8.928*** (1.266)	−0.413 (0.266)	−6.007*** (0.715)
as.factor(region)Respublika Dagestan	57.613*** (1.106)	50.880*** (1.242)	−2.124*** (0.261)	−28.635*** (0.702)
as.factor(region)Respublika Hakasiya	5.003*** (1.122)	3.520** (1.264)	−1.555*** (0.265)	−1.083 (0.714)
as.factor(region)Respublika Ingušetiya		55.359*** (1.822)		−29.678*** (1.029)
as.factor(region)Respublika Kalmykiya	37.498***	3.017	−1.274**	−3.050**

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(region)Respublika Kareliya	(1.662) 7.765***	(1.870) 3.889**	(0.393) 5.732***	(1.056) -16.653***
as.factor(region)Respublika Komi	(1.174) 7.231***	(1.316) 0.359	(0.278) -1.392***	(0.743) -4.209***
as.factor(region)Respublika Krym	(1.110) 43.133***	(1.242) 36.911***	(0.263) -2.450***	(0.702) -26.295***
as.factor(region)Respublika Marij Él	(1.643) 11.848***	(1.869) 0.116	(0.388) -2.314***	(1.056) 4.024***
as.factor(region)Respublika Mordoviya	(1.148) 46.963***	(1.290) 26.394***	(0.271) -2.610***	(0.729) -17.092***
as.factor(region)Respublika Saha (yakutiya)	(1.088) 11.962***	(1.225) 0.145	(0.257) -1.308***	(0.692) 2.649***
as.factor(region)Respublika Severnaya Osetiya - Alaniya	(1.053) 37.480***	(1.186) 43.331***	(0.249) -3.196***	(0.670) -22.167***
as.factor(region)Respublika Tatarstan (Tatarstan)	(1.053) 47.368***	(1.236) 46.877***	(0.260) -1.771***	(0.698) -23.080***
as.factor(region)Respublika Tyva	(1.053) 48.030***	(1.226) 48.916***	(0.257) -2.458***	(0.330) -25.905***
as.factor(region)Rostovskaya oblast	(1.053) 17.726***	(1.210) 10.384***	(0.257) -0.837***	(0.345) -6.558***
as.factor(region)Sahalinskaya oblast	(1.053) 8.741***	(1.194) 1.779	(0.257) -0.543*	(0.345) -0.872
as.factor(region)Samarskaya oblast	(1.053) 12.213***	(1.178) 6.641***	(0.257) 0.898***	(0.345) -5.285***
as.factor(region)Saratovskaya oblast	(1.053) 27.813***	(1.162) 15.944***	(0.257) 0.894**	(0.345) -6.312***

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(region)Smolenskaya oblast	(1.390) 9.371*** (0.702)	(1.593) 4.114*** (0.795)	(0.329) −0.672*** (0.166)	(0.900) −7.547*** (0.449)
as.factor(region)Stavropolskij kraj	21.731*** (0.836)	32.746*** (0.937)	−1.671*** (0.198)	−18.699*** (0.530)
as.factor(region)Sverdlovskaya oblast	5.624*** (0.536)	6.355*** (0.609)	0.735*** (0.127)	−11.921*** (0.344)
as.factor(region)Tambovskaya oblast	21.118*** (0.734)	20.894*** (0.831)	−0.930*** (0.174)	−17.618*** (0.470)
as.factor(region)Tomskaya oblast	7.964*** (0.676)	1.959* (0.769)	1.532*** (0.160)	−10.236*** (0.435)
as.factor(region)Tulskaya oblast	12.057*** (0.679)	17.524*** (0.771)	0.349* (0.160)	−14.674*** (0.435)
as.factor(region)Tümenskaya oblast	17.480*** (0.761)	15.401*** (0.857)	−2.242** (0.180)	−18.566*** (0.484)
as.factor(region)Tverskaya oblast	13.822*** (0.635)	1.361 (0.723)	−0.153 (0.150)	−7.642*** (0.408)
as.factor(region)Udmurtskaya Respublika	16.199*** (1.835)	3.219 (2.079)	−1.464*** (0.434)	−5.394*** (1.175)
as.factor(region)Ulyanovskaya oblast	5.048*** (0.816)	−1.362 (0.887)	−0.097 (0.193)	6.747*** (0.501)
as.factor(region)Vladimirskaya oblast	12.055*** (0.779)	7.682*** (0.878)	−0.662*** (0.184)	−6.133*** (0.496)
as.factor(region)Volgogradskaya oblast	15.308*** (0.630)	27.264*** (0.715)	−0.038 (0.149)	−18.094*** (0.404)
as.factor(region)Vologodskaya oblast	2.728***	3.648***	0.613***	−10.729***

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(region)Voronežskaya oblast	(0.719) 12.687***	(0.816) 11.233***	(0.170) −0.668***	(0.461) −6.489***
as.factor(region)Zabajkalskij kraj	(0.749) 1.826	(0.838) 5.989***	(0.177) −1.883***	(0.473) −10.565***
as.factor(market)02	(1.028) −1.138	(1.158) −2.228**	(0.243) 0.226	(0.654) 0.284
as.factor(market)03	(0.644) −2.010**	(0.715) −1.467*	(0.152) 0.647***	(0.404) −0.303
as.factor(market)05	(0.642) −2.816**	(0.714) −3.659***	(0.152) 1.387***	(0.403) 0.349
as.factor(market)06	(0.870) −1.334	(0.973) −1.761	(0.206) 1.074***	(0.550) −0.741
as.factor(market)07	(1.121) −1.238	(1.260) −2.696*	(0.265) 0.737**	(0.712) 0.231
as.factor(market)08	(0.629) −0.143	(0.700) −0.255	(0.149) 0.116	(0.396) −0.657
as.factor(market)09	(0.686) −1.173	(0.760) −1.430	(0.162) 0.635***	(0.429) −0.947*
as.factor(market)10	(0.617) 0.321	(0.687) 0.294	(0.146) 0.258	(0.388) −0.695
as.factor(market)11	(0.629) −1.680**	(0.696) −2.208**	(0.149) 0.449**	(0.393) −0.384
as.factor(market)12	(0.865) −0.244	(0.970) −1.520	(0.205) −0.098	(0.548) −0.517
as.factor(market)13		−1.432*	−0.328	0.474** −0.896*

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)14	(0.644) −0.844	(0.714) −0.923	(0.152) 0.586***	(0.403) −0.670
as.factor(market)15	(0.623) −1.003	(0.692) −0.288	(0.147) 0.413**	(0.391) −1.600***
as.factor(market)16	(0.650) 0.262	(0.723) −0.369	(0.154) 0.269	(0.408) −0.766
as.factor(market)17	(0.665) −0.986	(0.740) −1.995**	(0.157) 0.656***	(0.418) −0.404
as.factor(market)18	(0.629) −1.645**	(0.702) −1.090	(0.149) 0.823***	(0.397) −0.479
as.factor(market)19	(0.793) −4.379***	(0.869) −3.531***	(0.187) 1.087***	(0.491) 0.197
as.factor(market)20	(0.629) −0.776	(0.703) −1.060	(0.149) 0.555***	(0.397) −0.638
as.factor(market)21	(0.716) −3.129***	(0.797) −3.740***	(0.169) 1.296***	(0.450) −0.080
as.factor(market)22	(0.680) 0.419	(0.754) 0.281	(0.161) 0.193	(0.426) −0.790
as.factor(market)23	(0.673) 0.501	(0.741) −0.516	(0.159) 0.202	(0.419) −0.375
as.factor(market)24	(0.671) −1.531*	(0.752) −2.189**	(0.159) 0.485**	(0.425) −0.609
as.factor(market)25	(0.722) −0.015	(0.806) −1.799*	(0.171) −0.381*	(0.455) 0.216
as.factor(market)26	−3.415***	−3.347***	1.428***	−0.179

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)27	(0.621) −3.413***	(0.686) −1.568*	(0.147) 1.090***	(0.388) −0.444
as.factor(market)28	(0.669) −0.089	(0.741) −0.962	(0.158) 0.182	(0.419) −0.293
as.factor(market)29	(0.678) −2.552***	(0.754) −1.537*	(0.160) 1.293***	(0.426) −1.006*
as.factor(market)30	(0.696) −2.461***	(0.769) −2.761***	(0.165) 1.248***	(0.434) −0.055
as.factor(market)31	(0.660) 0.104	(0.731) −0.358	(0.156) 0.266	(0.413) −0.416
as.factor(market)32	(0.704) −2.704***	(0.784) −2.104**	(0.166) 0.531***	(0.443) −0.241
as.factor(market)33	(0.641) 0.291	(0.715) −1.214	(0.151) 0.151	(0.404) −0.344
as.factor(market)35	(0.638) −1.616**	(0.710) −0.767	(0.151) 0.271	(0.401) −0.699
as.factor(market)36	(0.612) −0.495	(0.679) −2.290**	(0.145) 0.585***	(0.383) −0.060
as.factor(market)37	(0.667) −2.386***	(0.726) −1.840*	(0.158) 0.597***	(0.410) −0.349
as.factor(market)38	(0.668) −0.795	(0.744) −0.111	(0.158) 0.209	(0.420) −0.671
as.factor(market)39	(0.668) 0.447	(0.750) −2.789*	(0.160) 0.793**	(0.424) −1.210
as.factor(market)41	(1.077) 0.800	(1.218) 1.276	(0.255) 0.170	(0.688) −0.989*

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)42	(0.746) 1.186	(0.829) 0.659	(0.176) −0.531***	(0.468) −0.354
as.factor(market)43	(0.631) 0.880	(0.704) −0.842	(0.149) 0.522**	(0.398) 0.214
as.factor(market)45	(0.726) 1.269	(0.799) 0.564	(0.172) 0.459**	(0.451) −0.792
as.factor(market)46	(0.733) 1.003	(0.813) 0.215	(0.173) 0.321	(0.459) −0.730
as.factor(market)47	(0.717) 2.561**	(0.801) 0.972	(0.169) −0.082	(0.453) −0.007
as.factor(market)49	(0.847) 2.516***	(0.948) 1.963*	(0.200) 0.145	(0.536) −1.063*
as.factor(market)50	(0.707) −3.114***	(0.790) −2.052*	(0.167) 1.173***	(0.446) −0.176
as.factor(market)51	(0.844) −2.905***	(0.924) −2.536**	(0.200) 1.238***	(0.522) 0.447
as.factor(market)52	(0.779) 0.530	(0.847) 0.177	(0.184) −0.153	(0.478) −0.096
as.factor(market)53	(0.693) −1.649**	(0.766) −2.331***	(0.164) 0.946***	(0.433) −0.549
as.factor(market)55	(0.629) −1.777**	(0.699) −2.164**	(0.149) 0.400**	(0.395) −0.075
as.factor(market)56	(0.652) 1.834*	(0.725) 1.091	(0.154) −0.017	(0.410) −0.235
as.factor(market)58	(0.724) −1.335*	(0.801) −2.019**	(0.171) 0.562***	(0.453) −0.544

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)59	(0.670) -2.302***	(0.737) -0.916	(0.158) 0.916***	(0.416) -0.565
as.factor(market)60	(0.694) -1.456*	(0.773) -0.352	(0.164) 0.306*	(0.437) -0.576
as.factor(market)61	(0.628) -2.071***	(0.702) -1.362*	(0.148) 0.930***	(0.397) -0.387
as.factor(market)62	(0.603) -0.434	(0.671) -0.858	(0.142) 0.545**	(0.379) -0.353
as.factor(market)63	(0.702) -1.807**	(0.774) -3.091***	(0.166) 0.360*	(0.437) 1.117**
as.factor(market)64	(0.673) 0.422	(0.745) -1.121	(0.159) 1.035***	(0.421) -0.614
as.factor(market)65	(0.639) -1.642*	(0.705) -2.586**	(0.151) 0.794***	(0.398) -0.247
as.factor(market)66	(0.639) -1.590*	(0.705) -1.204	(0.151) 0.975***	(0.398) -0.804
as.factor(market)68	(0.676) -0.272	(0.748) 1.133	(0.160) -0.176	(0.423) -0.875
as.factor(market)69	(0.762) 0.262	(0.850) -0.795	(0.180) 0.033	(0.480) -0.358
as.factor(market)70	(0.670) -3.084***	(0.748) -3.079***	(0.158) 1.581***	(0.423) -0.393
as.factor(market)71	0.098 (0.671)	-1.951** (0.750)	-0.451** (0.159)	0.756 (0.423)
as.factor(market)72	-1.154	-1.893*	1.124***	-0.909*

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)73	(0.713) −1.678*	(0.794) −1.209	(0.169) 0.142	(0.449) 0.272
as.factor(market)74	(0.730) −1.054	(0.815) −0.299	(0.173) 0.544**	(0.460) −0.931*
as.factor(market)75	(0.711) −3.500***	(0.787) −2.548***	(0.168) 0.940***	(0.445) −0.276
as.factor(market)77	(0.655) −0.968	(0.726) −2.351**	(0.155) 0.385*	(0.410) 0.292
as.factor(market)78	(0.708) −3.152***	(0.783) −1.158	(0.167) 0.852***	(0.443) −0.981*
as.factor(market)79	(0.741) 0.286	(0.823) 0.489	(0.175) 0.057	(0.465) −1.007*
as.factor(market)80	(0.749) −0.977	(0.824) 0.073	(0.177) 0.001	(0.466) −0.270
as.factor(market)81	(0.664) −1.345*	(0.729) −0.984	(0.157) 0.563***	(0.412) −0.481
as.factor(market)82	(0.676) 0.419	(0.750) 0.165	(0.160) −0.753***	(0.423) −0.879*
as.factor(market)84	(0.660) −1.362*	(0.723) 0.074	(0.156) 0.104	(0.409) −0.874*
as.factor(market)85	(0.669) 0.925	(0.742) −0.313	(0.158) −0.174	(0.419) −0.286
as.factor(market)86	(0.669) −3.204***	(0.744) −3.296***	(0.158) 1.044***	(0.420) −0.443
as.factor(market)87				

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)88	(0.708) −3.044***	(0.790) −1.318	(0.167) 1.126***	(0.446) −1.072*
as.factor(market)90	(0.696) −1.734*	(0.775) −2.317**	(0.165) 0.660***	(0.438) −0.281
as.factor(market)91	(0.709) −2.348**	(0.786) −4.117***	(0.168) 0.955***	(0.444) 0.567
as.factor(market)92	(0.794) −3.419***	(0.865) −3.492***	(0.188) 1.558***	(0.489) −0.358
as.factor(market)93	(0.736) −1.459*	(0.828) −0.911	(0.174) 0.333*	(0.468) −0.531
as.factor(market)94	(0.736) −2.909**	(0.991) −3.791***	(0.212) 1.282***	(0.560) −0.584
as.factor(market)95	(0.711) −2.909**	(0.797) −0.911	(0.168) 0.333*	(0.450) −0.531
as.factor(market)96	(0.711) −1.459*	(0.797) −0.911	(0.212) 0.333*	(0.560) −0.584
as.factor(market)97	(0.647) −6.510***	(0.720) −4.651***	(0.153) 1.989***	(0.406) 0.057
as.factor(market)98	(0.647) −0.913	(0.744) 0.213	(0.153) −0.421**	(0.406) −0.855*
as.factor(market)99	(1.077) −10.395***	(1.225) −8.090***	(0.254) 6.383***	(0.692) 0.057
uik_population	(10.021) −0.001***	(11.217) −0.001***	(2.369) 0.0002***	(6.337) 0.0002***
	(0.0001) −0.0001	(0.0001) −0.0001	(0.00001) 0.00001	(0.00003) −0.00003

Table 4: (continued)

	<i>Dependent variable:</i>			
	UR 2016	UR 2021	Yabloko 2016	Yabloko 2021
	(1)	(2)	(3)	(4)
Observations	31,439	33,564	31,439	33,564
R <sup>2</sup>	0.641	0.651	0.631	0.582
Adjusted R <sup>2</sup>	0.579	0.592	0.567	0.512

*Note:* \*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Table 5: Regression results (regional + sectoral fixed effects): vote share - Parliament

	<i>Dependent variable:</i>		
	SR 2016	SR 2021	NP 2021
	(1)	(2)	(3)
proximity	0.013 (0.058)	-0.315*** (0.047)	0.341*** (0.039)
as.factor(region)Yamalo-Neneckij avtonomnyj okrug	-11.613*** (0.363)	5.860*** (0.301)	-5.838*** (0.247)
as.factor(region)Amurskaya oblast	-10.122*** (0.394)	4.528*** (0.325)	1.475*** (0.267)
as.factor(region)Arhangelskaya oblast	-6.124*** (0.363)	3.209*** (0.297)	2.841*** (0.243)
as.factor(region)Yaroslavskaya oblast		-0.440 (0.244)	0.277 (0.200)
as.factor(region)Astrahanskaya oblast	5.136*** (0.444)	-2.555*** (0.367)	-0.745* (0.301)

as.factor(region)Belgorodskaya oblast	-4.776*** (0.342)	-1.330*** (0.281)	0.090 (0.230)
as.factor(region)Bryanskaya oblast	-11.267*** (0.349)	0.145 (0.287)	-4.874*** (0.236)
as.factor(region)Čečenskaya Respublika	-15.823*** (0.494)	-9.442*** (0.399)	-8.026*** (0.328)
as.factor(region)Čelyabinskaya oblast	3.720*** (0.210)	-0.774*** (0.174)	1.299*** (0.143)
as.factor(region)Čukotskij avtonomnyj okrug	-10.443*** (1.272)	11.601*** (1.060)	-1.762* (0.870)
as.factor(region)Čuvašskaya Respublika - Čuvašiya	-1.406*** (0.360)	-1.587*** (0.296)	-0.298 (0.243)
as.factor(region)Evrejskaya avtonomnaya oblast	-11.437*** (0.703)	2.373*** (0.586)	-2.705*** (0.481)
as.factor(region)gorod Moskva	-9.700*** (0.238)	-1.867*** (0.196)	-1.804*** (0.161)
as.factor(region)gorod Sankt-Peterburg	-8.920*** (0.246)	-2.924*** (0.203)	-0.171 (0.167)
as.factor(region)gorod Sevastopol	-10.892*** (0.523)	-0.292 (0.435)	-2.321*** (0.357)
as.factor(region)Habarovskij kraj	-11.340*** (0.363)	6.507*** (0.298)	0.479 (0.245)
as.factor(region)Irkutskaya oblast	-9.312*** (0.287)	-0.779*** (0.236)	3.111*** (0.194)
as.factor(region)Ivanovskaya oblast	-6.189*** (0.327)	-0.153 (0.269)	-0.885*** (0.221)
as.factor(region)Kabardino-Balkarskaya Respublika	-14.219*** (0.539)	-9.456*** (0.441)	-8.191*** (0.362)
as.factor(region)Kalingradskaya oblast	-9.416*** (0.339)	0.662* (0.279)	-0.521* (0.229)
as.factor(region)Kalužskaya oblast	-7.776*** (0.241)	-0.241 (0.638*)	

	(0.368)	(0.302)	(0.248)
as.factor(region)Kamčatskij kraj	-10.948*** (0.426)	3.940*** (0.354)	2.260*** (0.290)
as.factor(region)Karačaevo-Čerkesskaya Respublika	-15.921*** (0.625)	-7.463*** (0.514)	-7.019*** (0.422)
as.factor(region)Kemerovskaya oblast - Kuzbass		-2.581*** (0.223)	-5.475*** (0.183)
as.factor(region)Kirovskaya oblast	-4.157*** (0.307)	3.145*** (0.253)	1.562*** (0.208)
as.factor(region)Kostromskaya oblast	-5.816*** (0.375)	-0.018 (0.310)	1.035*** (0.255)
as.factor(region)Krasnoyarskij kraj	-10.433*** (0.243)	5.130*** (0.201)	0.635*** (0.165)
as.factor(region)Krasnodarskij kraj	-11.915*** (0.250)	-2.392*** (0.205)	-1.970*** (0.168)
as.factor(region)Kurganskaya oblast	-6.754*** (0.373)	1.574*** (0.289)	0.464 (0.237)
as.factor(region)Kurskaya oblast	-11.063*** (0.288)	2.233*** (0.239)	0.686*** (0.196)
as.factor(region)Leningradskaya oblast	-2.739*** (0.297)	0.079 (0.244)	-0.035 (0.201)
as.factor(region)Lipeckaya oblast	-12.066*** (1.903)	-1.615 (1.584)	-4.277** (1.300)
as.factor(region)Magadanskaya oblast	-6.424*** (0.635)	2.041*** (0.529)	0.456 (0.434)
as.factor(region)Moskovskaya oblast	-10.375*** (0.216)	-0.992*** (0.178)	-2.137*** (0.146)
as.factor(region)Murmanskaya oblast	-6.208*** (0.311)	2.801*** (0.257)	0.991*** (0.211)
as.factor(region)Neneckij avtonomnyj okrug	-10.398*** (1.140)	0.505 (0.818)	-0.547 (0.672)

as.factor(region)Nižegorodskaya oblast	-9.286*** (0.233)	-1.232*** (0.193)	-1.915*** (0.159)
as.factor(region)Novgorodskaya oblast	0.179 (0.361)	-0.874** (0.299)	0.979*** (0.246)
as.factor(region)Novosibirskaya oblast	-8.902*** (0.284)	0.637** (0.234)	2.102*** (0.192)
as.factor(region)Omskaya oblast	-7.059*** (0.248)	-2.145*** (0.206)	1.479*** (0.169)
as.factor(region)Orenburgskaya oblast	-8.108*** (0.253)	1.079*** (0.210)	-0.228 (0.172)
as.factor(region)Orlovskaya oblast	-7.074*** (0.354)	-0.572 (0.292)	0.572* (0.240)
as.factor(region)Penzenskaya oblast	-8.419*** (0.266)	0.618** (0.221)	-0.269 (0.181)
as.factor(region)Permskij kraj	-5.248*** (0.273)	1.810*** (0.224)	1.630*** (0.184)
as.factor(region)Primorskij kraj	-9.287*** (0.246)	-0.942*** (0.203)	-0.715*** (0.166)
as.factor(region)Pskovskaya oblast	-7.463*** (0.333)	-0.749** (0.277)	0.100 (0.228)
as.factor(region)Ryazanskaya oblast	-8.581*** (0.311)	0.723** (0.256)	-0.660** (0.210)
as.factor(region)Respublika Adygeya (Adygeya)	-9.298*** (0.636)	-3.638*** (0.519)	-4.109*** (0.426)
as.factor(region)Respublika Altaj	-11.201*** (0.924)	0.823 (0.763)	-0.963 (0.627)
as.factor(region)Respublika Baškortostan	-7.224*** (0.388)	-0.085 (0.314)	-3.365*** (0.258)
as.factor(region)Respublika Buryatiya	-7.163*** (0.459)	-4.578*** (0.377)	6.736*** (0.309)
as.factor(region)Respublika Dagestan	-12.893*** <hr/>	-5.146*** <hr/>	-8.497*** <hr/>

	(0.451)	(0.370)	(0.303)
as.factor(region)Respublika Hakasiya	-7.522*** (0.457)	-2.136*** (0.376)	3.304*** (0.309)
as.factor(region)Respublika Inguşetiya		-7.783*** (0.542)	-7.317*** (0.445)
as.factor(region)Respublika Kalmykiya	-13.844*** (0.677)	-6.457*** (0.557)	8.292*** (0.457)
as.factor(region)Respublika Kareliya	-6.194*** (0.479)	-0.697 (0.392)	-0.596 (0.321)
as.factor(region)Respublika Komi	-6.185*** (0.453)	1.580*** (0.370)	2.804*** (0.303)
as.factor(region)Respublika Krym	-13.779*** (0.670)	-2.848*** (0.556)	-3.002*** (0.457)
as.factor(region)Respublika Marij Él	-9.940*** (0.468)	-1.344*** (0.384)	0.458 (0.315)
as.factor(region)Respublika Mordoviya	-12.558*** (0.444)	0.673 (0.365)	-2.982*** (0.299)
as.factor(region)Respublika Saha (yakutiya)	-1.118** (0.429)	-4.035*** (0.353)	5.038*** (0.290)
as.factor(region)Respublika Severnaya Osetiya - Alaniya	-14.563*** (0.449)	-8.319*** (0.368)	-7.314*** (0.302)
as.factor(region)Respublika Tatarstan (Tatarstan)	-12.620*** (0.210)	-4.938*** (0.174)	-6.576*** (0.143)
as.factor(region)Respublika Tyva	-11.222*** (0.650)	-6.326*** (0.539)	-5.087*** (0.442)
as.factor(region)Rostovskaya oblast	-10.203*** (0.219)	-1.411*** (0.182)	-1.095*** (0.149)
as.factor(region)Sahalinskaya oblast	-11.630*** (0.372)	-0.047 (0.310)	3.190*** (0.254)
as.factor(region)Samarskaya oblast	-10.752*** (0.266)	-0.269 (0.214)	-1.246*** (0.175)

as.factor(region)Saratovskaya oblast	-10.054*** (0.566)	-3.616*** (0.474)	-2.716*** (0.389)
as.factor(region)Smolenskaya oblast	-9.373*** (0.286)	2.461*** (0.237)	-0.203 (0.194)
as.factor(region)Stavropol'skij kraj	-11.108*** (0.341)	-4.307*** (0.279)	-4.824*** (0.229)
as.factor(region)Sverdlovskaya oblast	-1.051*** (0.219)	-0.020 (0.181)	0.807*** (0.149)
as.factor(region)Tambovskaya oblast	-10.046*** (0.299)	-3.781*** (0.247)	-4.322*** (0.203)
as.factor(region)Tomskaya oblast	-6.849*** (0.275)	2.501*** (0.229)	2.653*** (0.188)
as.factor(region)Tulskaya oblast	-9.460*** (0.277)	-1.474*** (0.229)	-1.410*** (0.188)
as.factor(region)Tümenskaya oblast	-2.231*** (0.310)	4.509*** (0.255)	-1.991*** (0.209)
as.factor(region)Tverskaya oblast	-6.324*** (0.259)	0.850*** (0.215)	0.012 (0.177)
as.factor(region)Udmurtskaya Respublika	-6.768*** (0.748)	-0.522 (0.619)	-0.034 (0.508)
as.factor(region)Ulyanovskaya oblast	-11.455*** (0.333)	-0.300 (0.264)	-0.811*** (0.217)
as.factor(region)Vladimirskaya oblast	-7.269*** (0.318)	-0.263 (0.261)	0.129 (0.214)
as.factor(region)Volgogradskaya oblast	-9.207*** (0.257)	2.512*** (0.213)	-4.260*** (0.175)
as.factor(region)Vologodskaya oblast	-4.403*** (0.293)	3.022*** (0.243)	1.058*** (0.199)
as.factor(region)Voronežskaya oblast	-7.229*** (0.305)	-2.509*** (0.249)	-0.486* (0.205)
as.factor(region)Zabajkalskij kraj	-10.831***	1.725***	3.626***

	(0.419)	(0.345)	(0.283)
as.factor(market)02	0.348 (0.262)	0.314 (0.213)	0.615*** (0.175)
as.factor(market)03	1.404*** (0.261)	-0.364 (0.212)	0.776*** (0.174)
as.factor(market)05	2.071*** (0.355)	-0.628* (0.290)	0.930*** (0.238)
as.factor(market)06	-0.197 (0.457)	0.014 (0.375)	0.880** (0.308)
as.factor(market)07	0.284 (0.395)	0.056 (0.320)	0.249 (0.262)
as.factor(market)08	0.354 (0.256)	-0.115 (0.208)	0.452** (0.171)
as.factor(market)09	1.205*** (0.279)	-0.165 (0.226)	0.850*** (0.186)
as.factor(market)10	-0.098 (0.252)	-0.311 (0.204)	0.229 (0.168)
as.factor(market)11	0.779** (0.257)	0.185 (0.207)	0.420* (0.170)
as.factor(market)12	1.254*** (0.353)	-0.222 (0.289)	0.197 (0.237)
as.factor(market)13	0.830** (0.262)	-0.428* (0.212)	0.596*** (0.174)
as.factor(market)14	1.087*** (0.254)	-0.453* (0.206)	0.600*** (0.169)
as.factor(market)15	1.111*** (0.265)	-0.119 (0.215)	0.601*** (0.177)
as.factor(market)16	0.337 (0.271)	-0.183 (0.220)	0.150 (0.181)
as.factor(market)17	0.874*** (0.256)	-0.168 (0.209)	0.822*** (0.172)

as.factor(market)18	0.652*	-0.221	0.506**
as.factor(market)19	(0.254)	(0.206)	(0.169)
as.factor(market)20	1.592***	-0.246	0.903***
as.factor(market)21	(0.323)	(0.259)	(0.212)
as.factor(market)22	0.906***	-0.072	0.360*
as.factor(market)23	(0.256)	(0.209)	(0.172)
as.factor(market)24	0.940**	1.397***	0.206
as.factor(market)25	(0.292)	(0.237)	(0.195)
as.factor(market)26	0.183	-0.209	0.263
as.factor(market)27	(0.277)	(0.224)	(0.184)
as.factor(market)28	0.013	0.065	0.188
as.factor(market)29	(0.274)	(0.221)	(0.181)
as.factor(market)30	1.171***	0.047	0.573**
as.factor(market)31	(0.274)	(0.224)	(0.184)
as.factor(market)32	0.987***	0.102	0.299
as.factor(market)33	(0.294)	(0.240)	(0.197)
as.factor(market)26	1.119***	-0.360	0.806***
as.factor(market)27	(0.253)	(0.204)	(0.168)
as.factor(market)28	1.222***	-0.408	0.527**
as.factor(market)29	(0.273)	(0.221)	(0.181)
as.factor(market)30	0.598*	-0.198	0.606**
as.factor(market)31	(0.276)	(0.224)	(0.184)
as.factor(market)32	0.536	-0.373	0.893***
as.factor(market)33	(0.284)	(0.229)	(0.188)
as.factor(market)31	0.682*	-0.211	0.680***
as.factor(market)32	(0.269)	(0.218)	(0.179)
as.factor(market)33	0.940**	-0.356	0.486*
as.factor(market)31	(0.287)	(0.233)	(0.192)
as.factor(market)32	1.501***	-0.027	0.440*
as.factor(market)33	(0.261)	(0.213)	(0.175)
as.factor(market)33	0.404	-0.111	0.642***

	(0.260)	(0.211)	(0.173)
as.factor(market)35	0.665** (0.250)	0.064 (0.202)	0.141 (0.166)
as.factor(market)36	0.589* (0.272)	0.339 (0.216)	0.598*** (0.177)
as.factor(market)37	0.900*** (0.272)	-0.333 (0.221)	0.976*** (0.182)
as.factor(market)38	0.131 (0.275)	0.298 (0.223)	0.102 (0.183)
as.factor(market)39	0.915* (0.439)	0.416 (0.363)	0.278 (0.298)
as.factor(market)41	0.878** (0.304)	-0.738** (0.247)	0.212 (0.202)
as.factor(market)42	-0.051 (0.257)	-0.316 (0.210)	0.383* (0.172)
as.factor(market)43	0.350 (0.296)	-0.520* (0.238)	0.285 (0.195)
as.factor(market)45	-0.862** (0.299)	0.111 (0.242)	-0.201 (0.199)
as.factor(market)46	-0.124 (0.292)	-0.133 (0.239)	0.531** (0.196)
as.factor(market)47	-0.467 (0.345)	-0.346 (0.282)	0.157 (0.232)
as.factor(market)49	0.138 (0.288)	-0.580* (0.235)	-0.231 (0.193)
as.factor(market)50	0.860* (0.344)	-0.795** (0.275)	0.959*** (0.226)
as.factor(market)51	1.492*** (0.317)	-0.799** (0.252)	0.360 (0.207)
as.factor(market)52	0.146 (0.282)	-0.244 (0.228)	0.337 (0.187)

as.factor(market)53	0.791** (0.256)	0.106 (0.208)	0.486** (0.171)
as.factor(market)55	1.110*** (0.266)	0.218 (0.216)	0.651*** (0.177)
as.factor(market)56	-0.397 (0.295)	-0.144 (0.239)	0.018 (0.196)
as.factor(market)58	0.975*** (0.273)	-0.165 (0.219)	0.550** (0.180)
as.factor(market)59	1.155*** (0.283)	-0.458* (0.230)	0.389* (0.189)
as.factor(market)60	0.942*** (0.256)	-0.060 (0.209)	0.339* (0.172)
as.factor(market)61	1.487*** (0.246)	-0.354 (0.200)	0.387* (0.164)
as.factor(market)62	0.813** (0.286)	-0.567* (0.230)	0.442* (0.189)
as.factor(market)63	0.707** (0.274)	0.148 (0.222)	0.464* (0.182)
as.factor(market)64	0.359 (0.260)	-0.329 (0.210)	0.342* (0.172)
as.factor(market)65	1.322*** (0.326)	-0.136 (0.268)	0.349 (0.220)
as.factor(market)66	1.048*** (0.275)	-0.754*** (0.223)	0.623*** (0.183)
as.factor(market)68	0.374 (0.304)	-0.326 (0.246)	0.299 (0.202)
as.factor(market)69	0.244 (0.310)	0.013 (0.253)	0.182 (0.208)
as.factor(market)70	0.847** (0.273)	-0.051 (0.223)	0.618*** (0.183)
as.factor(market)71	0.128	0.152	0.678***

	(0.274)	(0.223)	(0.183)
as.factor(market)72	1.062*** (0.290)	-0.548* (0.236)	0.948*** (0.194)
as.factor(market)73	1.034*** (0.298)	-0.041 (0.243)	0.350 (0.199)
as.factor(market)74	1.091*** (0.290)	-0.219 (0.234)	0.462* (0.192)
as.factor(market)75	1.281*** (0.267)	-0.187 (0.216)	0.769*** (0.177)
as.factor(market)77	0.282 (0.289)	-0.123 (0.233)	0.693*** (0.191)
as.factor(market)78	1.438*** (0.302)	-0.565* (0.245)	0.983*** (0.201)
as.factor(market)79	0.418 (0.305)	-0.362 (0.245)	0.292 (0.201)
as.factor(market)80	0.202 (0.281)	-0.212 (0.228)	0.229 (0.187)
as.factor(market)81	0.846** (0.271)	-0.340 (0.217)	0.445* (0.178)
as.factor(market)82	0.799** (0.276)	0.495* (0.223)	0.388* (0.183)
as.factor(market)84	1.953*** (0.269)	-0.355 (0.215)	1.167*** (0.177)
as.factor(market)85	0.858** (0.273)	0.120 (0.221)	0.282 (0.181)
as.factor(market)86	0.083 (0.272)	0.500* (0.222)	0.222 (0.182)
as.factor(market)87	1.420*** (0.288)	-0.278 (0.235)	1.035*** (0.193)
as.factor(market)88	1.421*** (0.284)	-0.603** (0.231)	0.375* (0.189)

as.factor(market)90	1.105*** (0.289)	-0.407 (0.234)	0.816*** (0.192)
as.factor(market)91	1.088*** (0.324)	-0.130 (0.258)	1.125*** (0.211)
as.factor(market)92	1.077*** (0.300)	-1.143*** (0.247)	1.473*** (0.202)
as.factor(market)93	0.702* (0.290)	0.158 (0.237)	0.162 (0.195)
as.factor(market)94	2.429*** (0.366)	-0.497 (0.295)	0.950*** (0.242)
as.factor(market)95	0.713** (0.263)	-0.074 (0.214)	0.479** (0.176)
as.factor(market)96	0.366 (0.272)	0.041 (0.221)	0.277 (0.182)
as.factor(market)97	3.474*** (0.439)	-0.823* (0.365)	1.562*** (0.299)
as.factor(market)98	-2.731 (4.084)	-1.596 (3.339)	-0.490 (2.741)
as.factor(market)99	3.761*** (0.751)	-3.222*** (0.624)	5.216*** (0.512)
uik_population	0.0004*** (0.00002)	-0.0002*** (0.00002)	0.0002*** (0.00001)
Observations	31,439	33,564	33,564
R <sup>2</sup>	0.557	0.430	0.537
Adjusted R <sup>2</sup>	0.481	0.334	0.459

Note:

\*p<0.05; \*\*p<0.01; \*\*\*p<0.001

Table 6: Regression results (regional + sectoral fixed effects): vote share - President

	<i>Dependent variable:</i>			
	Putin 2012	Putin 2018	Zhirinovsky 2012	Zhirinovsky 2018
	(1)	(2)	(3)	(4)
proximity	−4.348*** (0.526)	−7.121*** (0.590)	−1.173* (0.532)	−1.466*** (0.226)
pop_hund	−0.297*** (0.028)	−0.426*** (0.032)	0.083* (0.034)	−0.085*** (0.012)
as.factor(market)02	−2.487* (1.038)	−4.998*** (1.175)	−4.016*** (0.851)	−0.955* (0.448)
as.factor(market)03	−3.548*** (1.034)	−2.970* (1.173)	−4.044*** (0.840)	−0.506 (0.446)
as.factor(market)05	−5.767*** (1.405)	−6.958*** (1.602)	−4.751*** (1.117)	−1.129 (0.606)
as.factor(market)06	−3.689* (1.813)	−4.804* (2.078)	−7.820*** (1.481)	−1.704* (0.778)
as.factor(market)07	−7.102*** (1.567)	−7.456*** (1.773)	−3.068* (1.452)	−2.830*** (0.673)
as.factor(market)08	−2.755** (1.017)	−3.834*** (1.155)	−4.333*** (0.849)	−0.465 (0.439)
as.factor(market)09	−6.166*** (1.103)	−5.745*** (1.248)	−6.348*** (0.977)	−1.635*** (0.475)
as.factor(market)10	−4.103*** (0.998)	−5.141*** (1.133)	−2.481** (0.832)	−1.233** (0.432)
as.factor(market)11	−3.836*** (1.017)	−5.016*** (1.147)	−2.607** (0.844)	−0.960* (0.439)
as.factor(market)12	−4.410** (1.397)	−6.382*** (1.596)	−9.873*** (1.256)	−0.647 (0.602)

Table 6: (continued)

	<i>Dependent variable:</i>			
	Putin 2012 (1)	Putin 2018 (2)	Zhirinovsky 2012 (3)	Zhirinovsky 2018 (4)
as.factor(market)13	-5.094*** (1.040)	-5.086*** (1.176)	-6.590*** (0.874)	-0.347 (0.449)
as.factor(market)14	-5.379*** (1.004)	-6.114*** (1.139)	-4.424*** (0.843)	-1.035* (0.434)
as.factor(market)15	-3.281** (1.047)	-2.429* (1.188)	-6.117*** (0.870)	-0.053 (0.450)
as.factor(market)16	-3.516** (1.075)	-5.142*** (1.221)	-3.684*** (0.902)	-0.831 (0.464)
as.factor(market)17	-5.857*** (1.014)	-8.380*** (1.155)	-6.717*** (0.866)	-0.502 (0.437)
as.factor(market)18	-5.971*** (1.009)	-6.256*** (1.143)	-4.422*** (0.845)	-1.309** (0.435)
as.factor(market)19	-4.694*** (1.282)	-2.827* (1.434)	-5.904*** (1.071)	-1.913*** (0.550)
as.factor(market)20	-6.001*** (1.015)	-7.901*** (1.158)	-5.713*** (0.874)	-1.500*** (0.438)
as.factor(market)21	-5.525*** (1.149)	-5.254*** (1.307)	-6.368*** (0.959)	-0.789 (0.495)
as.factor(market)22	-1.633 (1.100)	-2.679* (1.244)	-2.407** (0.903)	-0.735 (0.475)
as.factor(market)23	-0.905 (1.090)	-2.504* (1.225)	-2.564** (0.903)	-0.279 (0.470)
as.factor(market)24	-4.869*** (1.083)	-8.005*** (1.238)	-5.983*** (0.923)	0.048 (0.468)
as.factor(market)25	-2.228 (1.169)	-6.084*** (1.330)	-4.974*** (1.006)	-0.432 (0.503)

Table 6: (continued)

	<i>Dependent variable:</i>			
	Putin 2012 (1)	Putin 2018 (2)	Zhirinovsky 2012 (3)	Zhirinovsky 2018 (4)
as.factor(market)26	-9.052*** (1.002)	-9.287*** (1.130)	-6.286*** (0.875)	-2.121*** (0.431)
as.factor(market)27	-4.586*** (1.081)	-4.296*** (1.221)	-6.629*** (0.906)	-1.247** (0.466)
as.factor(market)28	-2.932** (1.094)	-5.591*** (1.241)	-4.530*** (0.895)	-0.193 (0.472)
as.factor(market)29	-6.391*** (1.119)	-6.378*** (1.262)	-6.782*** (1.000)	-1.547** (0.480)
as.factor(market)30	-7.527*** (1.061)	-9.522*** (1.200)	-7.515*** (0.920)	-2.093*** (0.456)
as.factor(market)31	-4.521*** (1.139)	-6.183*** (1.295)	-6.270*** (0.937)	-1.223* (0.493)
as.factor(market)32	-6.600*** (1.033)	-8.905*** (1.176)	-6.559*** (0.876)	-0.464 (0.446)
as.factor(market)33	-4.203*** (1.029)	-7.271*** (1.169)	-5.175** (0.875)	-1.275** (0.445)
as.factor(market)35	-2.706** (0.988)	-1.941 (1.117)	-2.086* (0.848)	-0.548 (0.427)
as.factor(market)36	-3.672*** (1.076)	-4.854*** (1.196)	-5.287*** (0.882)	-1.151* (0.463)
as.factor(market)37	-6.435*** (1.079)	-6.371*** (1.225)	-8.433*** (0.883)	-1.150* (0.464)
as.factor(market)38	-2.011 (1.088)	-2.250 (1.233)	-2.787** (0.900)	0.804 (0.469)
as.factor(market)39	-0.259 (1.736)	-5.883** (2.002)	-8.597*** (1.406)	0.616 (0.751)

Table 6: (continued)

	<i>Dependent variable:</i>			
	Putin 2012 (1)	Putin 2018 (2)	Zhirinovsky 2012 (3)	Zhirinovsky 2018 (4)
as.factor(market)41	1.508 (1.163)	4.083** (1.319)	4.672*** (0.927)	1.413** (0.503)
as.factor(market)42	-2.884** (1.019)	-5.986*** (1.160)	-0.854 (0.930)	-0.844 (0.440)
as.factor(market)43	6.503*** (1.163)	4.611*** (1.308)	3.837*** (0.962)	1.569** (0.502)
as.factor(market)45	-1.775 (1.185)	-2.274 (1.341)	-2.826** (1.022)	-0.320 (0.511)
as.factor(market)46	12.102*** (1.109)	13.192*** (1.267)	9.032*** (0.910)	4.534*** (0.479)
as.factor(market)47	4.800*** (1.354)	3.506* (1.548)	1.367 (1.101)	1.308* (0.586)
as.factor(market)49	1.639 (1.134)	-1.571 (1.293)	2.193* (1.007)	0.491 (0.491)
as.factor(market)50	-8.192*** (1.364)	-8.295*** (1.523)	-9.770*** (1.122)	-2.627*** (0.587)
as.factor(market)51	-2.872* (1.254)	-2.514 (1.391)	-6.358*** (1.053)	-1.131* (0.534)
as.factor(market)52	-0.113 (1.123)	-0.449 (1.268)	-1.106 (0.957)	0.517 (0.485)
as.factor(market)53	-5.539*** (1.016)	-7.521*** (1.152)	-7.551*** (0.870)	-1.239** (0.437)
as.factor(market)55	-5.426*** (1.055)	-7.528*** (1.197)	-4.532*** (0.868)	-1.608*** (0.455)
as.factor(market)56	-0.538 (1.168)	-2.041 (1.320)	-2.205* (0.939)	-0.475 (0.505)

Table 6: (continued)

	<i>Dependent variable:</i>			
	Putin 2012 (1)	Putin 2018 (2)	Zhirinovsky 2012 (3)	Zhirinovsky 2018 (4)
as.factor(market)58	-6.002*** (1.082)	-6.942*** (1.214)	-6.059*** (0.873)	-1.121* (0.466)
as.factor(market)59	-5.873*** (1.121)	-5.413*** (1.275)	-5.973*** (0.926)	-1.553** (0.484)
as.factor(market)60	-3.460*** (1.012)	-2.738* (1.155)	-3.646** (0.829)	-1.061* (0.437)
as.factor(market)61	-5.580*** (0.974)	-5.806*** (1.107)	-2.948*** (0.807)	-1.560*** (0.420)
as.factor(market)62	-4.234*** (1.137)	-5.577*** (1.278)	-4.397*** (0.961)	-0.789 (0.491)
as.factor(market)63	-5.425*** (1.090)	-7.530*** (1.232)	-4.799*** (0.910)	-1.460** (0.469)
as.factor(market)64	-3.353** (1.027)	-4.216*** (1.157)	-5.961*** (0.867)	-1.296** (0.441)
as.factor(market)65	1.506 (1.171)	-2.320 (1.347)	-3.312** (1.150)	2.296*** (0.505)
as.factor(market)66	-5.473*** (1.092)	-6.300*** (1.233)	-3.491*** (0.922)	-1.897*** (0.469)
as.factor(market)68	1.895 (1.187)	3.502** (1.343)	4.010*** (1.037)	0.774 (0.513)
as.factor(market)69	-0.983 (1.233)	-3.305* (1.404)	-1.189 (1.066)	-0.856 (0.532)
as.factor(market)70	-6.669*** (1.082)	-8.442*** (1.232)	-2.602** (0.908)	-2.478*** (0.468)
as.factor(market)71	-0.199 (1.081)	-2.545* (1.232)	0.273 (0.930)	0.888 (0.467)

Table 6: (continued)

	<i>Dependent variable:</i>			
	Putin 2012 (1)	Putin 2018 (2)	Zhirinovsky 2012 (3)	Zhirinovsky 2018 (4)
as.factor(market)72	-5.774*** (1.150)	-7.924*** (1.307)	-5.587*** (0.981)	-0.623 (0.496)
as.factor(market)73	-3.086** (1.183)	-4.408** (1.346)	-2.647** (0.968)	-0.222 (0.509)
as.factor(market)74	-3.846*** (1.151)	-4.361*** (1.300)	-3.808*** (0.943)	-0.019 (0.496)
as.factor(market)75	-8.895*** (1.054)	-9.130*** (1.192)	-8.625*** (0.869)	-1.727*** (0.453)
as.factor(market)77	-4.291*** (1.142)	-6.151*** (1.290)	-2.154* (1.024)	-0.993* (0.493)
as.factor(market)78	-6.493*** (1.197)	-5.102*** (1.357)	-5.417*** (0.995)	-1.229* (0.517)
as.factor(market)79	-3.542** (1.211)	-5.140*** (1.359)	-2.805** (0.987)	-1.365** (0.520)
as.factor(market)80	-3.190** (1.114)	-1.388 (1.261)	-1.086 (0.929)	-0.701 (0.481)
as.factor(market)81	-4.478*** (1.076)	-3.045* (1.204)	-4.110*** (0.877)	-1.259** (0.465)
as.factor(market)82	-3.708*** (1.092)	-5.245*** (1.235)	-4.681*** (0.964)	-0.476 (0.470)
as.factor(market)84	-7.141*** (1.065)	-8.334*** (1.190)	-7.304*** (0.891)	-1.500*** (0.455)
as.factor(market)85	-5.482*** (1.083)	-6.408*** (1.224)	-4.379*** (0.873)	-0.946* (0.467)
as.factor(market)86	1.374 (1.083)	-1.201 (1.230)	0.233 (0.873)	0.013 (0.468)

Table 6: (continued)

	<i>Dependent variable:</i>			
	Putin 2012	Putin 2018	Zhirinovsky 2012	Zhirinovsky 2018
	(1)	(2)	(3)	(4)
as.factor(market)87	-3.097** (1.139)	-4.512*** (1.297)	-3.265*** (0.923)	0.030 (0.492)
as.factor(market)88	-5.359*** (1.122)	-5.557*** (1.274)	-8.220*** (0.930)	-0.911 (0.484)
as.factor(market)90	-4.012*** (1.147)	-5.966*** (1.297)	-6.457*** (0.930)	-1.039* (0.493)
as.factor(market)91	-6.411*** (1.281)	-8.178*** (1.425)	-9.919*** (1.063)	-1.670** (0.551)
as.factor(market)92	-7.836*** (1.181)	-9.730*** (1.356)	-11.730*** (1.031)	-2.139*** (0.510)
as.factor(market)93	-3.863*** (1.152)	-6.450*** (1.317)	-1.703 (0.935)	-0.985* (0.498)
as.factor(market)94	-9.686*** (1.451)	-9.315*** (1.632)	-9.847*** (1.264)	-3.154*** (0.627)
as.factor(market)95	-2.252* (1.046)	-5.457*** (1.187)	-2.252** (0.865)	-0.468 (0.452)
as.factor(market)96	-4.270*** (1.079)	-3.919** (1.228)	-3.281*** (0.905)	-0.622 (0.466)
as.factor(market)97	1.395 (1.730)	0.831 (2.009)	-5.078*** (1.409)	-0.929 (0.747)
as.factor(market)98	-14.633 (16.308)	-1.971 (18.620)	4.373 (12.725)	-11.618 (7.059)
as.factor(market)99	-15.901*** (2.962)	-15.057*** (3.437)	-11.804*** (2.274)	-3.564** (1.282)
proximity:pop_hund	0.218***	0.299***	0.008	0.065***

Table 6: (continued)

	<i>Dependent variable:</i>			
	Putin 2012	Putin 2018	Zhirinovsky 2012	Zhirinovsky 2018
	(1)	(2)	(3)	(4)
	(0.019)	(0.021)	(0.021)	(0.008)
Observations	31,439	33,564	24,539	31,998
R <sup>2</sup>	0.052	0.046	0.082	0.029
Adjusted R <sup>2</sup>	-0.107	-0.110	-0.091	-0.139
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001			

Table 7: Regression results (regional + sectoral fixed effects): vote share - President

	<i>Dependent variable:</i>			
	Mironov 2012	Yavlinsky 2018	Prohorov 2012	Sobchak 2018
	(1)	(2)	(3)	(4)
proximity	0.053 (0.030)	0.070*** (0.013)	-0.335*** (0.072)	0.126*** (0.016)
as.factor(region)Yamalo-Neneckij avtonomnyj okrug	-3.236*** (0.564)	-0.182* (0.080)	-7.328*** (1.337)	-0.189 (0.103)
as.factor(region)Amurskaya oblast	-1.512*** (0.199)	-0.238** (0.087)	-4.973*** (0.472)	0.348** (0.112)
as.factor(region)Arhangelskaya oblast	1.314*** (0.165)	0.475*** (0.079)	2.380*** (0.391)	1.071*** (0.102)
as.factor(region)Astrahanskaya oblast	-0.878*** (0.222)	0.031 (0.098)	-5.658*** (0.526)	0.468*** (0.126)

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(region)Belgorodskaya oblast	0.043 (0.157)	-0.158* (0.075)	-2.767*** (0.373)	0.138 (0.097)
as.factor(region)Bryanskaya oblast	-0.643*** (0.159)	-0.275*** (0.077)	-3.722*** (0.378)	0.057 (0.099)
as.factor(region)Čečenskaya Respublika	-4.704*** (0.226)	-0.034 (0.108)	-11.241*** (0.537)	-0.027 (0.139)
as.factor(region)Čelyabinskaya oblast	1.476*** (0.092)	0.651*** (0.046)	0.807*** (0.219)	0.829*** (0.059)
as.factor(region)Čukotskij avtonomnyj okrug	-1.866*** (0.555)	-0.184 (0.280)	1.087 (1.316)	-0.079 (0.360)
as.factor(region)Čuvašskaya Respublika - Čuvašiya	2.698*** (0.349)	0.082 (0.079)	0.891 (0.827)	0.731*** (0.102)
as.factor(region)Evrejskaya avtonomnaya oblast	-0.596 (0.307)	-0.437** (0.155)	-0.536 (0.728)	-0.340 (0.199)
as.factor(region)gorod Moskva		2.501*** (0.052)		3.173*** (0.067)
as.factor(region)gorod Sankt-Peterburg		2.805*** (0.054)		3.778*** (0.070)
as.factor(region)gorod Sevastopol		-0.489*** (0.115)		0.009 (0.148)
as.factor(region)Habarovskij kraj	0.761*** (0.168)	-0.142 (0.080)	-0.285 (0.399)	0.481*** (0.103)
as.factor(region)Irkutskaya oblast	-0.575*** (0.132)	-0.022 (0.063)	-0.994** (0.313)	0.195* (0.081)
as.factor(region)Ivanovskaya oblast	0.063	0.122	-1.810***	0.711***

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(region)Kabardino-Balkarskaya Respublika	(0.153) −1.853*** (0.253)	(0.072) −0.814*** (0.118)	(0.363) −8.471*** (0.600)	(0.092) −1.059*** (0.152)
as.factor(region)Kaliningradskaya oblast	−0.925*** (0.157)	0.892*** (0.074)	3.605*** (0.374)	1.756*** (0.096)
as.factor(region)Kalužskaya oblast		0.330*** (0.081)		0.583*** (0.104)
as.factor(region)Kamčatskij kraj	−1.151*** (0.185)	−0.239* (0.094)	0.063 (0.440)	−0.129 (0.121)
as.factor(region)Karačaevo-Čerkesskaya Respublika	−3.714*** (0.288)	−0.676*** (0.137)	−9.493*** (0.683)	−0.720*** (0.177)
as.factor(region)Kirovskaya oblast	0.880*** (0.140)	0.359*** (0.067)	1.082** (0.333)	0.871*** (0.087)
as.factor(region)Kostromskaya oblast	0.123 (0.168)	0.245** (0.082)	−1.923*** (0.399)	0.495*** (0.106)
as.factor(region)Krasnoyarskij kraj	−0.463*** (0.108)	0.170** (0.053)	0.302 (0.257)	0.573*** (0.069)
as.factor(region)Krasnodarskij kraj	−0.339** (0.115)	0.048 (0.054)	0.776** (0.273)	0.174* (0.070)
as.factor(region)Kurganskaya oblast	−1.252*** (0.157)	−0.436*** (0.082)	−4.290*** (0.372)	−0.179 (0.105)
as.factor(region)Kurskaya oblast	−0.127 (0.127)	−0.304*** (0.063)	−1.548*** (0.302)	−0.160* (0.082)
as.factor(region)Leningradskaya oblast	1.539*** (0.132)	0.500*** (0.065)	0.985** (0.314)	1.110*** (0.084)
as.factor(region)Lipeckaya oblast		−0.572		−0.884

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(region)Magadanskaya oblast		(0.419)		(0.539)
	-0.642*	-0.216	1.562*	-0.006
	(0.278)	(0.140)	(0.659)	(0.180)
as.factor(region)Moskovskaya oblast	0.031	0.738***	1.806***	1.139***
	(0.097)	(0.047)	(0.231)	(0.061)
as.factor(region)Murmanskaya oblast	0.909***	0.330***	1.087**	1.050***
	(0.140)	(0.068)	(0.333)	(0.088)
as.factor(region)Neneckij avtonomnyj okrug	1.427**	-0.339	2.952*	0.104
	(0.497)	(0.251)	(1.180)	(0.323)
as.factor(region)Nižegorodskaya oblast	-1.291***	0.297***	-3.676***	0.670***
	(0.108)	(0.051)	(0.257)	(0.066)
as.factor(region)Novgorodskaya oblast	2.305***	1.096***	1.363*	1.124***
	(0.269)	(0.079)	(0.638)	(0.102)
as.factor(region)Novosibirskaya oblast	-1.158***	0.465***	-0.661*	0.656***
	(0.129)	(0.062)	(0.307)	(0.080)
as.factor(region)Omskaya oblast	0.293**	0.196***	-0.498	0.642***
	(0.110)	(0.055)	(0.260)	(0.070)
as.factor(region)Orenburgskaya oblast	0.133	0.054	-2.022***	0.345***
	(0.112)	(0.056)	(0.266)	(0.071)
as.factor(region)Orlovskaya oblast	-0.647***	-0.019	-1.810***	0.413***
	(0.157)	(0.078)	(0.373)	(0.100)
as.factor(region)Penzenskaya oblast	-0.634***	0.037	-1.830***	0.336***
	(0.116)	(0.058)	(0.276)	(0.075)
as.factor(region)Permskij kraj	0.548***	0.895***	3.696***	1.516***
	(0.135)	(0.060)	(0.321)	(0.077)
as.factor(region)Primorskij kraj	0.120	0.307***	-0.692*	0.797***

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(region)Pskovskaya oblast	(0.119) 0.237	(0.054) 1.284***	(0.282) 0.281	(0.069) 0.831***
as.factor(region)Ryazanskaya oblast	(0.146) −0.061	(0.073) 0.108	(0.346) −2.279***	(0.094) 0.518***
as.factor(region)Respublika Adygeya (Adygeya)	(0.138) −1.289***	(0.068) −0.217	(0.327) −3.308***	(0.088) −0.054
as.factor(region)Respublika Altaj	(0.295) −0.407	(0.139) −0.369	(0.701) −1.346	(0.179) −0.213
as.factor(region)Respublika Baškortostan	(0.418) −1.315***	(0.203) 0.195*	(0.991) −5.394***	(0.262) 0.322**
as.factor(region)Respublika Buryatiya	(0.187) −0.993***	(0.085) 0.588***	(0.444) −1.504**	(0.109) 1.506***
as.factor(region)Respublika Dagestan	(0.211) −3.962***	(0.099) −0.507***	(0.502) −9.920***	(0.128) −0.504***
as.factor(region)Respublika Hakasiya	(0.209) −0.728***	(0.100) −0.208*	(0.497) −1.016*	(0.129) 0.317*
as.factor(region)Respublika Kalmykiya	(0.313) −1.528***	(0.149) 0.021	(0.742) −2.531***	(0.191) 0.864***
as.factor(region)Respublika Kareliya	(0.230) 1.054***	(0.105) 1.022***	(0.547) 3.017***	(0.135) 1.184***
as.factor(region)Respublika Komi	(0.213) −0.373	(0.099) 0.130	(0.505) −1.142*	(0.128) 0.935***
as.factor(region)Respublika Krym			(0.147) −0.650***	0.173 (0.189)
as.factor(region)Respublika Marij Él	0.096	−0.196	−1.968***	0.472***

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(region)Respublika Mordoviya	(0.217) −3.647*** (0.204)	(0.103) −0.377*** (0.097)	(0.515) −8.060*** (0.485)	(0.132) 0.068 (0.125)
as.factor(region)Respublika Saha (yakutiya)	0.194 (0.198)	−0.281** (0.094)	−2.153*** (0.469)	0.796*** (0.121)
as.factor(region)Respublika Severnaya Osetiya - Alaniya	−1.498*** (0.207)	−0.840*** (0.099)	−8.399*** (0.491)	−1.004*** (0.127)
as.factor(region)Respublika Tatarstan (Tatarstan)	−2.003*** (0.092)	0.310*** (0.046)	−4.835*** (0.219)	0.440*** (0.059)
as.factor(region)Respublika Tyva	−2.928*** (0.291)	−0.689*** (0.143)	−8.919*** (0.690)	0.035 (0.184)
as.factor(region)Rostovskaya oblast	−0.816*** (0.097)	0.058 (0.048)	−2.915*** (0.231)	0.144* (0.062)
as.factor(region)Sahalinskaya oblast	−0.300 (0.167)	0.069 (0.082)	2.207*** (0.397)	0.612*** (0.105)
as.factor(region)Samarskaya oblast	−0.614 (0.314)	0.738*** (0.057)	−3.238*** (0.744)	1.281*** (0.073)
as.factor(region)Saratovskaya oblast	−0.735** (0.263)	1.413*** (0.125)	−0.415 (0.625)	1.876*** (0.160)
as.factor(region)Smolenskaya oblast	0.253* (0.125)	0.181** (0.063)	−0.744* (0.296)	0.514*** (0.081)
as.factor(region)Stavropol'skij kraj	−1.353*** (0.159)	−0.409*** (0.075)	−3.159*** (0.378)	−0.281** (0.096)
as.factor(region)Sverdlovskaya oblast	1.676*** (0.097)	0.611*** (0.048)	3.344*** (0.230)	1.070*** (0.062)
as.factor(region)Tambovskaya oblast	−1.641***	0.089	−3.461***	0.196*

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(region)Tomskaya oblast	(0.130) −0.704*** (0.120)	(0.066) 0.713*** (0.061)	(0.309) 4.076*** (0.285)	(0.085) 1.344*** (0.078)
as.factor(region)Tulskaya oblast		0.604*** (0.061)		0.756*** (0.078)
as.factor(region)Tūmenskaya oblast	−1.988*** (0.267)	−0.078 (0.068)	−3.590*** (0.634)	0.603*** (0.087)
as.factor(region)Tverskaya oblast	0.335** (0.114)	0.177** (0.057)	0.299 (0.269)	0.490*** (0.073)
as.factor(region)Udmurtskaya Respublika	−0.406 (0.335)	−0.161 (0.165)	0.651 (0.795)	0.365 (0.212)
as.factor(region)Ulyanovskaya oblast		0.092 (0.070)		0.217* (0.090)
as.factor(region)Vladimirskaya oblast	2.493*** (0.146)	0.075 (0.070)	1.389*** (0.347)	0.504*** (0.090)
as.factor(region)Volgogradskaya oblast	0.607*** (0.115)	0.318*** (0.056)	−2.457*** (0.273)	0.233** (0.073)
as.factor(region)Vologodskaya oblast	2.344*** (0.131)	0.835*** (0.064)	0.935** (0.311)	1.403*** (0.083)
as.factor(region)Voronežskaya oblast	0.098 (0.144)	0.102 (0.067)	−1.847*** (0.341)	0.323*** (0.086)
as.factor(region)Zabajkalskij kraj	−2.125*** (0.215)	−0.376*** (0.092)	−6.999*** (0.510)	−0.067 (0.118)
as.factor(market)02	0.126 (0.125)	0.170** (0.058)	1.349*** (0.297)	0.209** (0.074)
as.factor(market)03	0.342**	0.413***	1.671***	0.473***

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(market)05	(0.123) 0.263	(0.057) 0.857***	(0.293) 2.297***	(0.074) 1.049***
as.factor(market)06	(0.163) 0.389	(0.078) 0.385***	(0.387) 2.413***	(0.100) 0.621***
as.factor(market)07	(0.216) 0.319	(0.100) 0.282**	(0.511) 1.169*	(0.128) 0.556***
as.factor(market)08	(0.212) 0.016	(0.086) 0.209***	(0.502) 0.962**	(0.111) 0.246***
as.factor(market)09	(0.124) 0.198	(0.056) 0.393***	(0.295) 1.665***	(0.072) 0.407***
as.factor(market)10	(0.143) 0.002	(0.061) 0.170**	(0.339) 0.227	(0.079) 0.248***
as.factor(market)11	(0.122) 0.008	(0.055) 0.203***	(0.289) 0.625*	(0.071) 0.288***
as.factor(market)12	(0.122) 0.370*	(0.055) 0.248**	(0.289) 1.753***	(0.071) 0.153
as.factor(market)13	(0.124) 0.290*	(0.056) 0.252***	(0.293) 1.332***	(0.073) 0.371***
as.factor(market)14	(0.123) 0.053	(0.056) 0.263***	(0.293) 1.180***	(0.072) 0.328***
as.factor(market)15	(0.128) 0.277*	(0.058) 0.282***	(0.304) 2.273***	(0.075) 0.480***
as.factor(market)16	(0.132) −0.009	(0.060) 0.134*	(0.313) 0.568	(0.077) 0.164*
as.factor(market)17	(0.115) 0.115	(0.386***) 0.386***	(1.573***) 1.573***	(0.496***) 0.496***

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(market)18	(0.127) 0.150	(0.056) 0.378***	(0.301) 1.231***	(0.072) 0.416***
as.factor(market)19	(0.123) 0.452**	(0.056) 0.546***	(0.293) 2.598***	(0.072) 0.801***
as.factor(market)20	(0.156) 0.025	(0.071) 0.292***	(0.371) 1.687***	(0.091) 0.433***
as.factor(market)21	(0.128) 0.341*	(0.056) 0.563***	(0.304) 2.563***	(0.072) 0.796***
as.factor(market)22	(0.142) 0.125	(0.064) 0.161**	(0.336) 0.566	(0.082) 0.175*
as.factor(market)23	(0.132) 0.085	(0.060) 0.113	(0.312) 0.959**	(0.077) 0.162*
as.factor(market)24	(0.135) 0.048	(0.060) 0.283***	(0.321) 1.398***	(0.077) 0.397***
as.factor(market)25	(0.147) 0.309*	(0.064) −0.005	(0.348) 1.256***	(0.083) 0.055
as.factor(market)26	(0.128) 0.221	(0.055) 0.615***	(0.304) 2.793***	(0.071) 0.753***
as.factor(market)27	(0.133) 0.280*	(0.060) 0.488***	(0.315) 1.915***	(0.077) 0.637***
as.factor(market)28	(0.131) 0.099	(0.061) 0.108	(0.311) 1.065***	(0.078) 0.354***
as.factor(market)29	(0.146) 0.233	(0.062) 0.567***	(0.347) 2.861***	(0.080) 0.665***
as.factor(market)30	(0.086) 0.086	(0.494***) 0.494***	(1.583***) 1.583***	(0.698***) 0.698***

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(market)31	(0.135) 0.147	(0.059) 0.151*	(0.320) 0.929**	(0.076) 0.181*
as.factor(market)32	(0.137) 0.433***	(0.063) 0.279***	(0.324) 1.691***	(0.081) 0.299***
as.factor(market)33	(0.128) 0.190	(0.057) 0.160**	(0.305) 0.812**	(0.074) 0.178*
as.factor(market)35	(0.124) 0.061	(0.055) 0.260***	(0.294) 0.510	(0.071) 0.273***
as.factor(market)36	(0.129) 0.109	(0.060) 0.324***	(0.307) 1.602***	(0.077) 0.352***
as.factor(market)37	(0.129) 0.359**	(0.060) 0.331***	(0.307) 2.315***	(0.077) 0.539***
as.factor(market)38	(0.131) −0.069	(0.060) 0.141*	(0.312) 0.716*	(0.078) 0.128
as.factor(market)39	(0.206) 0.269	(0.097) 0.521***	(0.488) 2.448***	(0.124) 0.709***
as.factor(market)41	(0.141) −0.260	(0.067) 0.075	(0.336) 0.103	(0.086) 0.129
as.factor(market)42	(0.135) −0.032	(0.057) −0.072	(0.321) 0.005	(0.073) −0.002
as.factor(market)43	(0.142) 0.077	(0.065) 0.193**	(0.337) 0.240	(0.084) 0.281***
as.factor(market)45	(0.149) 0.303*	(0.066) 0.121	(0.354) 0.173	(0.084) 0.128
as.factor(market)46	(0.200) 0.200	(0.112) 0.453	(0.453) 0.291***	

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(market)47	(0.140) −0.093	(0.064) 0.068	(0.333) 0.050	(0.083) 0.020
as.factor(market)49	(0.163) −0.209	(0.076) 0.044	(0.386) −0.246	(0.098) 0.093
as.factor(market)50	(0.149) 0.191	(0.063) 0.574***	(0.352) 2.677***	(0.082) 0.717***
as.factor(market)51	(0.164) 0.361*	(0.075) 0.641***	(0.389) 2.083***	(0.097) 0.738***
as.factor(market)52	(0.155) 0.406**	(0.069) −0.003	(0.367) 0.559	(0.089) 0.062
as.factor(market)53	(0.139) 0.295*	(0.062) 0.453***	(0.331) 2.330***	(0.080) 0.567***
as.factor(market)55	(0.127) 0.241	(0.056) 0.206***	(0.302) 1.440***	(0.072) 0.332***
as.factor(market)56	(0.127) −0.013	(0.058) 0.004	(0.301) 0.667*	(0.075) −0.055
as.factor(market)58	(0.128) 0.384**	(0.060) 0.270***	(0.303) 1.999***	(0.077) 0.425***
as.factor(market)59	(0.135) 0.114	(0.062) 0.383***	(0.321) 1.455***	(0.080) 0.574***
as.factor(market)60	(0.122) 0.031	(0.056) 0.228***	(0.289) 0.848**	(0.072) 0.192**
as.factor(market)61	(0.118) 0.157	(0.054) 0.449***	(0.281) 1.356***	(0.069) 0.573***
as.factor(market)62	(0.210) 0.210	(0.274***) 0.274***	(1.157***) 1.157***	(0.364***) 0.364***

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(market)63	(0.140) −0.047	(0.063) 0.234***	(0.333) 1.072***	(0.081) 0.189*
as.factor(market)64	(0.133) 0.258*	(0.060) 0.526***	(0.315) 2.110***	(0.077) 0.535***
as.factor(market)65	(0.128) 0.264	(0.057) 0.406***	(0.302) 0.905*	(0.073) 0.466***
as.factor(market)66	(0.187) 0.109	(0.071) 0.377***	(0.444) 1.254***	(0.092) 0.616***
as.factor(market)68	(0.154) −0.151	(0.067) 0.026	(0.366) −0.006	(0.086) 0.011
as.factor(market)69	(0.155) 0.133	(0.068) 0.090	(0.368) 0.326	(0.088) 0.089
as.factor(market)70	(0.133) 0.032	(0.060) 0.622***	(0.315) 0.893**	(0.077) 0.661***
as.factor(market)71	(0.136) −0.199	(0.060) −0.081	(0.322) −0.090	(0.077) −0.058
as.factor(market)72	(0.144) 0.386**	(0.064) 0.486***	(0.341) 2.582***	(0.082) 0.554***
as.factor(market)73	(0.141) 0.079	(0.065) 0.078	(0.335) 0.451	(0.084) 0.121
as.factor(market)74	(0.138) −0.003	(0.064) 0.211***	(0.326) 1.274***	(0.082) 0.438***
as.factor(market)75	(0.128) 0.222	(0.058) 0.490***	(0.303) 1.981***	(0.075) 0.624***
as.factor(market)77	(−0.059) −0.059	(0.350***) 0.350***	(0.038) 0.038	(0.282***) 0.282***

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(market)78	(0.149) −0.066	(0.063) 0.440***	(0.354) 1.649***	(0.082) 0.552***
as.factor(market)79	(0.146) −0.079	(0.066) 0.070	(0.345) 0.620	(0.085) 0.150
as.factor(market)80	(0.144) 0.019	(0.067) 0.084	(0.342) 0.464	(0.086) 0.018
as.factor(market)81	(0.136) 0.090	(0.062) 0.239***	(0.322) 1.159***	(0.079) 0.343***
as.factor(market)82	(0.128) 0.218	(0.060) −0.147*	(0.304) 1.033**	(0.077) −0.001
as.factor(market)84	(0.131) 0.330*	(0.059) 0.509***	(0.310) 1.958***	(0.075) 0.676***
as.factor(market)85	(0.128) 0.288*	(0.060) 0.146*	(0.303) 0.673*	(0.077) 0.172*
as.factor(market)86	(0.127) 0.052	(0.060) 0.006	(0.302) −0.042	(0.077) −0.023
as.factor(market)87	(0.135) 0.168	(0.063) 0.507***	(0.321) 2.038***	(0.082) 0.676***
as.factor(market)88	(0.136) 0.271*	(0.062) 0.548***	(0.323) 2.727***	(0.080) 0.661***
as.factor(market)90	(0.136) 0.238	(0.063) 0.441***	(0.323) 1.640***	(0.081) 0.572***
as.factor(market)91	(0.156) 0.368*	(0.071) 0.562***	(0.369) 3.333***	(0.091) 0.773***
as.factor(market)92		0.476** 0.787***	5.340*** 1.038***	

Table 7: (continued)

	<i>Dependent variable:</i>			
	Mironov 2012 (1)	Yavlinsky 2018 (2)	Prohorov 2012 (3)	Sobchak 2018 (4)
as.factor(market)93	(0.152) -0.005	(0.066) 0.252***	(0.360) 0.564	(0.085) 0.204*
as.factor(market)94	(0.136) 0.448*	(0.064) 0.647***	(0.323) 2.214***	(0.082) 0.914***
as.factor(market)95	(0.185) 0.148	(0.081) 0.148*	(0.438) 0.572	(0.104) 0.144
as.factor(market)96	(0.127) 0.177	(0.058) -0.031	(0.300) 0.751*	(0.075) -0.016
as.factor(market)97	0.707*** (0.207)	1.004*** (0.096)	4.379*** (0.491)	1.226*** (0.124)
as.factor(market)98	-3.868* (1.837)	-0.001 (0.900)	-7.660 (4.358)	-0.400 (1.158)
as.factor(market)99	0.889** (0.333)	2.483*** (0.166)	9.808*** (0.790)	2.679*** (0.213)
uik_population	0.0001*** (0.00001)	0.0001*** (0.00000)	0.001*** (0.00003)	0.0001*** (0.00001)
Observations	24,539	31,998	24,539	31,998
R <sup>2</sup>	0.366	0.512	0.390	0.483
Adjusted R <sup>2</sup>	0.243	0.425	0.271	0.392

*Note:*

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

Table 8: Regression results (regional + sectoral fixed effects): vote share - President

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
proximity	0.332*** (0.098)	0.397*** (0.053)
as.factor(region)Yamalo-Neneckij avtonomnyj okrug	-18.250*** (1.819)	-17.883*** (0.329)
as.factor(region)Amurskaya oblast	-7.558*** (0.643)	-1.950*** (0.358)
as.factor(region)Arhangelskaya oblast	-6.147*** (0.533)	-12.907*** (0.327)
as.factor(region)Astrahanskaya oblast	-9.191*** (0.715)	-7.028*** (0.403)
as.factor(region)Belgorodskaya oblast	1.748*** (0.508)	-10.747*** (0.310)
as.factor(region)Bryanskaya oblast	0.247 (0.514)	-13.217*** (0.316)
as.factor(region)Čečenskaya Respublika	-24.057*** (0.730)	-13.745*** (0.446)
as.factor(region)Čelyabinskaya oblast	-6.504*** (0.298)	-11.119*** (0.190)
as.factor(region)Čukotskij avtonomnyj okrug	-9.657*** (1.791)	-17.323*** (1.156)
as.factor(region)Čuvaškaya Respublika - Čuvašiya	-0.445 (1.126)	-9.667*** (0.326)
as.factor(region)Evrejskaya avtonomnaya oblast	-3.205** (0.991)	-5.056*** (0.640)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(region)gorod Moskva		-10.667*** (0.215)
as.factor(region)gorod Sankt-Peterburg		-14.345*** (0.223)
as.factor(region)gorod Sevastopol		-20.463*** (0.475)
as.factor(region)Habarovskij kraj	-4.686*** (0.542)	-3.147*** (0.329)
as.factor(region)Irkutskaya oblast	-1.175** (0.426)	-6.603*** (0.260)
as.factor(region)Ivanovskaya oblast	-4.265*** (0.493)	-7.540*** (0.297)
as.factor(region)Kabardino-Balkarskaya Respublika	-11.934*** (0.816)	-17.794*** (0.489)
as.factor(region)Kalininogradskaya oblast	-1.808*** (0.508)	-11.663*** (0.307)
as.factor(region)Kalužskaya oblast		-12.195*** (0.334)
as.factor(region)Kamčatskij kraj	-6.465*** (0.598)	-6.375*** (0.388)
as.factor(region)Karačaevo-Čerkesskaya Respublika	-19.215*** (0.929)	-14.451*** (0.567)
as.factor(region)Kirovskaya oblast	-3.310*** (0.453)	-9.397*** (0.278)
as.factor(region)Kostromskaya oblast	2.853** (0.542)	-7.100*** (0.340)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(region)Krasnoyarskij kraj	-3.945*** (0.350)	-10.485*** (0.220)
as.factor(region)Krasnodarskij kraj	-1.103** (0.372)	-12.975*** (0.225)
as.factor(region)Kurganskaya oblast	-3.223*** (0.507)	-9.498*** (0.338)
as.factor(region)Kurskaya oblast	-2.623*** (0.411)	-14.976*** (0.262)
as.factor(region)Leningradskaya oblast	-7.946*** (0.427)	-13.814*** (0.268)
as.factor(region)Lipeckaya oblast		-8.324*** (1.731)
as.factor(region)Magadanskaya oblast	-1.954* (0.897)	-10.163*** (0.577)
as.factor(region)Moskovskaya oblast	-2.221*** (0.314)	-10.419*** (0.195)
as.factor(region)Murmanskaya oblast	-6.202*** (0.453)	-14.315*** (0.283)
as.factor(region)Neneckij avtonomnyj okrug	-4.346** (1.606)	-9.563*** (1.037)
as.factor(region)Nižegorodskaya oblast	-3.797*** (0.349)	-12.570*** (0.212)
as.factor(region)Novgorodskaya oblast	-4.430*** (0.869)	-9.149*** (0.328)
as.factor(region)Novosibirskaya oblast	0.189 (0.417)	-5.835*** (0.258)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(region)Omskaya oblast	2.952*** (0.354)	-1.320*** (0.225)
as.factor(region)Orenburgskaya oblast	3.616*** (0.362)	-8.150*** (0.229)
as.factor(region)Orlovskaya oblast	8.882*** (0.507)	-10.094*** (0.321)
as.factor(region)Penza kraj	-1.288*** (0.376)	-13.433*** (0.241)
as.factor(region)Permskij kraj	-5.874*** (0.437)	-12.968*** (0.246)
as.factor(region)Primorskij kraj	-1.473*** (0.384)	-1.197*** (0.222)
as.factor(region)Pskovskaya oblast	-1.237** (0.471)	-12.494*** (0.303)
as.factor(region)Ryazanskaya oblast	-0.149 (0.445)	-9.526*** (0.282)
as.factor(region)Respublika Adygeya (Adygeya)	-3.920*** (0.953)	-7.423*** (0.575)
as.factor(region)Respublika Altaj	-5.579*** (1.348)	3.489*** (0.839)
as.factor(region)Respublika Baškortostan	-7.630*** (0.604)	-9.797*** (0.350)
as.factor(region)Respublika Buryatiya	-5.669*** (0.698)	-6.218*** (0.417)
as.factor(region)Respublika Dagestan	-16.338*** (0.683)	-12.408*** (0.410)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(region)Respublika Hakasiya	-1.898** (0.676)	-2.242*** (0.415)
as.factor(region)Respublika Kalmykiya	-7.973*** (1.009)	-9.650*** (0.614)
as.factor(region)Respublika Kareliya	-7.242*** (0.744)	-10.320*** (0.434)
as.factor(region)Respublika Komi	-10.462*** (0.686)	-10.506*** (0.410)
as.factor(region)Respublika Krym		-19.971*** (0.608)
as.factor(region)Respublika Marij Él	-0.618 (0.701)	-7.343*** (0.424)
as.factor(region)Respublika Mordoviya	-19.295*** (0.659)	-12.987*** (0.402)
as.factor(region)Respublika Saha (yakutiya)	-9.777*** (0.638)	4.582*** (0.390)
as.factor(region)Respublika Severnaya Osetiya - Alaniya	-4.125*** (0.668)	-10.865*** (0.407)
as.factor(region)Respublika Tatarstan (Tatarstan)	-10.363*** (0.298)	-13.445*** (0.190)
as.factor(region)Respublika Tyva	-17.932*** (0.939)	-17.935*** (0.591)
as.factor(region)Rostovskaya oblast	-2.360*** (0.314)	-11.538*** (0.198)
as.factor(region)Sahalinskaya oblast	-1.163* (0.540)	-4.043*** (0.338)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(region)Samarskaya oblast	4.370*** (1.012)	-11.777*** (0.235)
as.factor(region)Saratovskaya oblast	-7.510*** (0.850)	-11.395*** (0.514)
as.factor(region)Smolenskaya oblast	1.412*** (0.402)	-10.680*** (0.259)
as.factor(region)Stavropolskij kraj	-5.571*** (0.514)	-11.767*** (0.309)
as.factor(region)Sverdlovskaya oblast	-9.183*** (0.313)	-11.839*** (0.198)
as.factor(region)Tambovskaya oblast	-3.368*** (0.421)	-13.516*** (0.271)
as.factor(region)Tomskaya oblast	-3.180*** (0.387)	-8.755*** (0.250)
as.factor(region)Tulskaya oblast		-14.251** (0.251)
as.factor(region)Tûmenskaya oblast	-11.617*** (0.863)	-14.484*** (0.280)
as.factor(region)Tverskaya oblast	-3.917*** (0.367)	-12.412*** (0.235)
as.factor(region)Udmurtskaya Respublika	-6.869*** (1.082)	-3.850*** (0.680)
as.factor(region)Ulyanovskaya oblast		-7.607*** (0.289)
as.factor(region)Vladimirskaya oblast	-1.305** (0.472)	-10.049*** (0.288)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(region)Volgogradskaya oblast	-2.036*** (0.371)	-11.750*** (0.233)
as.factor(region)Vologodskaya oblast	-6.472*** (0.423)	-11.371*** (0.266)
as.factor(region)Voronežskaya oblast	2.791*** (0.463)	-10.597*** (0.276)
as.factor(region)Zabajkalskij kraj	-8.402*** (0.694)	-7.911*** (0.379)
as.factor(market)02	0.390 (0.404)	-0.647** (0.238)
as.factor(market)03	0.890* (0.398)	-0.504* (0.237)
as.factor(market)05	-0.518 (0.527)	-1.350*** (0.322)
as.factor(market)06	0.865 (0.696)	-0.817* (0.412)
as.factor(market)07	-1.291 (0.683)	-0.613 (0.356)
as.factor(market)08	0.134 (0.401)	-1.161*** (0.233)
as.factor(market)09	0.754 (0.462)	-1.300*** (0.253)
as.factor(market)10	-0.192 (0.393)	-1.066*** (0.229)
as.factor(market)11	-0.122 (0.399)	-0.705** (0.233)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(market)12	1.058 (0.592)	-1.716*** (0.320)
as.factor(market)13	0.217 (0.413)	-0.904*** (0.238)
as.factor(market)14	0.566 (0.398)	-0.854*** (0.230)
as.factor(market)15	0.556 (0.413)	-1.403*** (0.239)
as.factor(market)16	-0.022 (0.426)	-1.124*** (0.246)
as.factor(market)17	0.650 (0.410)	-1.188*** (0.232)
as.factor(market)18	0.144 (0.399)	-0.733** (0.230)
as.factor(market)19	0.244 (0.505)	-0.704* (0.291)
as.factor(market)20	-0.371 (0.413)	-1.169*** (0.232)
as.factor(market)21	0.975* (0.457)	-1.302*** (0.264)
as.factor(market)22	0.166 (0.426)	-1.152*** (0.252)
as.factor(market)23	0.378 (0.425)	-0.548* (0.248)
as.factor(market)24	1.253** (0.437)	-1.686*** (0.248)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(market)25	1.206* (0.473)	-0.726** (0.266)
as.factor(market)26	0.059 (0.414)	-0.880*** (0.229)
as.factor(market)27	0.800 (0.428)	-0.678** (0.247)
as.factor(market)28	0.451 (0.423)	-0.872*** (0.250)
as.factor(market)29	0.025 (0.472)	-0.371 (0.256)
as.factor(market)30	0.795 (0.436)	-1.025*** (0.243)
as.factor(market)31	0.636 (0.441)	-0.755** (0.261)
as.factor(market)32	0.704 (0.414)	-1.001*** (0.237)
as.factor(market)33	0.518 (0.414)	-0.911*** (0.236)
as.factor(market)35	-0.098 (0.400)	-0.433 (0.226)
as.factor(market)36	0.131 (0.418)	-0.814*** (0.246)
as.factor(market)37	0.874* (0.417)	-0.610* (0.246)
as.factor(market)38	0.662 (0.424)	-0.773** (0.249)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(market)39	2.792*** (0.664)	-1.630*** (0.399)
as.factor(market)41	0.325 (0.457)	-0.841** (0.277)
as.factor(market)42	-0.593 (0.437)	-0.535* (0.233)
as.factor(market)43	0.230 (0.459)	-0.121 (0.268)
as.factor(market)45	0.241 (0.481)	-0.643* (0.271)
as.factor(market)46	0.318 (0.453)	-1.338*** (0.265)
as.factor(market)47	0.469 (0.525)	-1.155*** (0.314)
as.factor(market)49	-0.199 (0.479)	-1.102*** (0.262)
as.factor(market)50	0.690 (0.529)	-0.798* (0.311)
as.factor(market)51	0.419 (0.499)	-0.582* (0.284)
as.factor(market)52	0.321 (0.450)	-0.402 (0.256)
as.factor(market)53	0.937* (0.411)	-1.086*** (0.232)
as.factor(market)55	0.347 (0.410)	-0.498* (0.241)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(market)56	0.273 (0.444)	-0.588* (0.268)
as.factor(market)58	0.215 (0.413)	-0.787** (0.247)
as.factor(market)59	0.563 (0.437)	-0.737** (0.257)
as.factor(market)60	-0.042 (0.394)	-0.721** (0.232)
as.factor(market)61	-0.079 (0.382)	-0.693** (0.223)
as.factor(market)62	-0.092 (0.453)	-0.580* (0.260)
as.factor(market)63	1.048* (0.429)	-0.251 (0.248)
as.factor(market)64	0.549 (0.412)	-0.951*** (0.235)
as.factor(market)65	1.231* (0.604)	-1.142*** (0.295)
as.factor(market)66	0.144 (0.435)	-0.589* (0.249)
as.factor(market)68	0.163 (0.497)	-0.381 (0.276)
as.factor(market)69	0.091 (0.501)	-0.387 (0.281)
as.factor(market)70	0.564 (0.429)	-0.212 (0.248)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(market)71	-0.591 (0.438)	-0.556* (0.249)
as.factor(market)72	0.220 (0.464)	-1.202*** (0.263)
as.factor(market)73	0.344 (0.456)	0.056 (0.269)
as.factor(market)74	-0.095 (0.444)	-1.216*** (0.262)
as.factor(market)75	0.626 (0.412)	-0.978*** (0.241)
as.factor(market)77	1.128* (0.482)	-0.210 (0.262)
as.factor(market)78	-0.289 (0.470)	-0.808** (0.274)
as.factor(market)79	-0.909 (0.466)	-0.689* (0.276)
as.factor(market)80	-0.532 (0.438)	-0.010 (0.255)
as.factor(market)81	0.176 (0.413)	-0.544* (0.246)
as.factor(market)82	0.714 (0.454)	-0.906*** (0.249)
as.factor(market)84	0.958* (0.421)	-0.553* (0.242)
as.factor(market)85	0.318 (0.412)	-0.759** (0.247)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
as.factor(market)86	-0.219 (0.411)	-0.413 (0.247)
as.factor(market)87	-0.674 (0.437)	-1.551*** (0.262)
as.factor(market)88	0.795 (0.440)	-1.025*** (0.257)
as.factor(market)90	0.242 (0.439)	-0.889*** (0.261)
as.factor(market)91	1.048* (0.502)	-0.929** (0.293)
as.factor(market)92	2.188*** (0.490)	-1.133*** (0.272)
as.factor(market)93	-0.179 (0.440)	-0.544* (0.263)
as.factor(market)94	1.367* (0.596)	-1.176*** (0.332)
as.factor(market)95	0.301 (0.409)	-0.734** (0.239)
as.factor(market)96	0.357 (0.426)	-0.837*** (0.246)
as.factor(market)97	1.308 (0.668)	-0.882* (0.398)
as.factor(market)98	-7.080 (5.929)	3.041 (3.715)
as.factor(market)99	0.298 (1.075)	-0.820 (0.684)

Table 8: (continued)

	<i>Dependent variable:</i>	
	Zuganov 2012	Grudinin 2018
	(1)	(2)
uik_population	0.0003*** (0.00004)	0.00004* (0.00002)
Observations	24,539	31,998
R <sup>2</sup>	0.439	0.556
Adjusted R <sup>2</sup>	0.330	0.478
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001	

Table 9: Regression results (regional + sectoral fixed effects): vote share - UR+Putin

	<i>Dependent variable:</i>			
	UR 2016	UR 2021	Putin 2012	Putin 2018
	(1)	(2)	(3)	(4)
proximity	-4.348*** (0.526)	-7.121*** (0.590)	-1.173* (0.532)	-1.466*** (0.226)
pop_hund	-0.297*** (0.028)	-0.426*** (0.032)	0.083* (0.034)	-0.085*** (0.012)
as.factor(market)02	-2.487* (1.038)	-4.998*** (1.175)	-4.016*** (0.851)	-0.955* (0.448)
as.factor(market)03	-3.548*** (1.034)	-2.970* (1.173)	-4.044*** (0.840)	-0.506 (0.446)
as.factor(market)05	-5.767*** (1.405)	-6.958*** (1.602)	-4.751*** (1.117)	-1.129 (0.606)

Table 9: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)06	-3.689* (1.813)	-4.804* (2.078)	-7.820*** (1.481)	-1.704* (0.778)
as.factor(market)07	-7.102*** (1.567)	-7.456*** (1.773)	-3.068* (1.452)	-2.830*** (0.673)
as.factor(market)08	-2.755** (1.017)	-3.834*** (1.155)	-4.333*** (0.849)	-0.465 (0.439)
as.factor(market)09	-6.166*** (1.103)	-5.745*** (1.248)	-6.348*** (0.977)	-1.635*** (0.475)
as.factor(market)10	-4.103*** (0.998)	-5.141*** (1.133)	-2.481** (0.832)	-1.233** (0.432)
as.factor(market)11	-3.836*** (1.017)	-5.016*** (1.147)	-2.607** (0.844)	-0.960* (0.439)
as.factor(market)12	-4.410** (1.397)	-6.382*** (1.596)	-9.873*** (1.256)	-0.647 (0.602)
as.factor(market)13	-5.094*** (1.040)	-5.086*** (1.176)	-6.590*** (0.874)	-0.347 (0.449)
as.factor(market)14	-5.379*** (1.004)	-6.114*** (1.139)	-4.424*** (0.843)	-1.035* (0.434)
as.factor(market)15	-3.281** (1.047)	-2.429* (1.188)	-6.117*** (0.870)	-0.053 (0.450)
as.factor(market)16	-3.516** (1.075)	-5.142*** (1.221)	-3.684*** (0.902)	-0.831 (0.464)
as.factor(market)17	-5.857*** (1.014)	-8.380*** (1.155)	-6.717*** (0.866)	-0.502 (0.437)
as.factor(market)18	-5.971*** (1.009)	-6.256*** (1.143)	-4.422*** (0.845)	-1.309** (0.435)

Table 9: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)19	-4.694*** (1.282)	-2.827* (1.434)	-5.904*** (1.071)	-1.913*** (0.550)
as.factor(market)20	-6.001*** (1.015)	-7.901*** (1.158)	-5.713*** (0.874)	-1.500*** (0.438)
as.factor(market)21	-5.525*** (1.149)	-5.254*** (1.307)	-6.368*** (0.959)	-0.789 (0.495)
as.factor(market)22	-1.633 (1.100)	-2.679* (1.244)	-2.407** (0.903)	-0.735 (0.475)
as.factor(market)23	-0.905 (1.090)	-2.504* (1.225)	-2.564** (0.903)	-0.279 (0.470)
as.factor(market)24	-4.869*** (1.083)	-8.005*** (1.238)	-5.983*** (0.923)	0.048 (0.468)
as.factor(market)25	-2.228 (1.169)	-6.084*** (1.330)	-4.974*** (1.006)	-0.432 (0.503)
as.factor(market)26	-9.052*** (1.002)	-9.287*** (1.130)	-6.286*** (0.875)	-2.121*** (0.431)
as.factor(market)27	-4.586*** (1.081)	-4.296*** (1.221)	-6.629*** (0.906)	-1.247** (0.466)
as.factor(market)28	-2.932** (1.094)	-5.591*** (1.241)	-4.530*** (0.895)	-0.193 (0.472)
as.factor(market)29	-6.391*** (1.119)	-6.378*** (1.262)	-6.782*** (1.000)	-1.547** (0.480)
as.factor(market)30	-7.527*** (1.061)	-9.529*** (1.200)	-7.515*** (0.920)	-2.093*** (0.456)
as.factor(market)31	-4.521*** (1.139)	-6.183*** (1.295)	-6.270*** (0.937)	-1.223* (0.493)

Table 9: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)32	-6.600*** (1.033)	-8.905*** (1.176)	-6.559*** (0.876)	-0.464 (0.446)
as.factor(market)33	-4.203*** (1.029)	-7.271*** (1.169)	-5.175*** (0.875)	-1.275** (0.445)
as.factor(market)35	-2.706** (0.988)	-1.941 (1.117)	-2.086* (0.848)	-0.548 (0.427)
as.factor(market)36	-3.672*** (1.076)	-4.854*** (1.196)	-5.287*** (0.882)	-1.151* (0.463)
as.factor(market)37	-6.435*** (1.079)	-6.371*** (1.225)	-8.433*** (0.883)	-1.150* (0.464)
as.factor(market)38	-2.011 (1.088)	-2.250 (1.233)	-2.787** (0.900)	0.804 (0.469)
as.factor(market)39	-0.259 (1.736)	-5.883** (2.002)	-8.597*** (1.406)	0.616 (0.751)
as.factor(market)41	1.508 (1.163)	4.083** (1.319)	4.672*** (0.927)	1.413** (0.503)
as.factor(market)42	-2.884** (1.019)	-5.986*** (1.160)	-0.854 (0.930)	-0.844 (0.440)
as.factor(market)43	6.503*** (1.163)	4.611*** (1.308)	3.837*** (0.962)	1.569** (0.502)
as.factor(market)45	-1.775 (1.185)	-2.274 (1.341)	-2.826** (1.022)	-0.320 (0.511)
as.factor(market)46	12.102*** (1.109)	13.192*** (1.267)	9.032*** (0.910)	4.534*** (0.479)
as.factor(market)47	4.800*** (1.354)	3.506* (1.548)	1.367 (1.101)	1.308* (0.586)

Table 9: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)49	1.639 (1.134)	-1.571 (1.293)	2.193* (1.007)	0.491 (0.491)
as.factor(market)50	-8.192*** (1.364)	-8.295*** (1.523)	-9.770*** (1.122)	-2.627*** (0.587)
as.factor(market)51	-2.872* (1.254)	-2.514 (1.391)	-6.358*** (1.053)	-1.131* (0.534)
as.factor(market)52	-0.113 (1.123)	-0.449 (1.268)	-1.106 (0.957)	0.517 (0.485)
as.factor(market)53	-5.539*** (1.016)	-7.521*** (1.152)	-7.551*** (0.870)	-1.239** (0.437)
as.factor(market)55	-5.426*** (1.055)	-7.528*** (1.197)	-4.532*** (0.868)	-1.608*** (0.455)
as.factor(market)56	-0.538 (1.168)	-2.041 (1.320)	-2.205* (0.939)	-0.475 (0.505)
as.factor(market)58	-6.002*** (1.082)	-6.942*** (1.214)	-6.059*** (0.873)	-1.121* (0.466)
as.factor(market)59	-5.873*** (1.121)	-5.413*** (1.275)	-5.973*** (0.926)	-1.553** (0.484)
as.factor(market)60	-3.460*** (1.012)	-2.738* (1.155)	-3.646*** (0.829)	-1.061* (0.437)
as.factor(market)61	-5.580*** (0.974)	-5.806*** (1.107)	-2.948*** (0.807)	-1.560*** (0.420)
as.factor(market)62	-4.234*** (1.137)	-5.577*** (1.278)	-4.397*** (0.961)	-0.789 (0.491)
as.factor(market)63	-5.425*** (1.090)	-7.530*** (1.232)	-4.799*** (0.910)	-1.460** (0.469)

Table 9: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)64	-3.353** (1.027)	-4.216*** (1.157)	-5.961*** (0.867)	-1.296** (0.441)
as.factor(market)65	1.506 (1.171)	-2.320 (1.347)	-3.312** (1.150)	2.296*** (0.505)
as.factor(market)66	-5.473*** (1.092)	-6.300*** (1.233)	-3.491*** (0.922)	-1.897*** (0.469)
as.factor(market)68	1.895 (1.187)	3.502** (1.343)	4.010*** (1.037)	0.774 (0.513)
as.factor(market)69	-0.983 (1.233)	-3.305* (1.404)	-1.189 (1.066)	-0.856 (0.532)
as.factor(market)70	-6.669*** (1.082)	-8.442*** (1.232)	-2.602** (0.908)	-2.478*** (0.468)
as.factor(market)71	-0.199 (1.081)	-2.545* (1.232)	0.273 (0.930)	0.888 (0.467)
as.factor(market)72	-5.774*** (1.150)	-7.924*** (1.307)	-5.587*** (0.981)	-0.623 (0.496)
as.factor(market)73	-3.086** (1.183)	-4.408** (1.346)	-2.647** (0.968)	-0.222 (0.509)
as.factor(market)74	-3.846*** (1.151)	-4.361*** (1.300)	-3.808*** (0.943)	-0.019 (0.496)
as.factor(market)75	-8.895*** (1.054)	-9.130*** (1.192)	-8.625*** (0.869)	-1.727*** (0.453)
as.factor(market)77	-4.291*** (1.142)	-6.151*** (1.290)	-2.154* (1.024)	-0.993* (0.493)
as.factor(market)78	-6.493*** (1.197)	-5.102*** (1.357)	-5.417*** (0.995)	-1.229* (0.517)

Table 9: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)79	-3.542** (1.211)	-5.140*** (1.359)	-2.805** (0.987)	-1.365** (0.520)
as.factor(market)80	-3.190** (1.114)	-1.388 (1.261)	-1.086 (0.929)	-0.701 (0.481)
as.factor(market)81	-4.478*** (1.076)	-3.045* (1.204)	-4.110*** (0.877)	-1.259** (0.465)
as.factor(market)82	-3.708*** (1.092)	-5.245*** (1.235)	-4.681*** (0.964)	-0.476 (0.470)
as.factor(market)84	-7.141*** (1.065)	-8.334*** (1.190)	-7.304*** (0.891)	-1.500*** (0.455)
as.factor(market)85	-5.482*** (1.083)	-6.408*** (1.224)	-4.379*** (0.873)	-0.946* (0.467)
as.factor(market)86	1.374 (1.083)	-1.201 (1.230)	0.233 (0.873)	0.013 (0.468)
as.factor(market)87	-3.097** (1.139)	-4.512*** (1.297)	-3.265*** (0.923)	0.030 (0.492)
as.factor(market)88	-5.359*** (1.122)	-5.557*** (1.274)	-8.220*** (0.930)	-0.911 (0.484)
as.factor(market)90	-4.012*** (1.147)	-5.966*** (1.297)	-6.457*** (0.930)	-1.039* (0.493)
as.factor(market)91	-6.411*** (1.281)	-8.178*** (1.425)	-9.919*** (1.063)	-1.670** (0.551)
as.factor(market)92	-7.836*** (1.181)	-9.730*** (1.356)	-11.730*** (1.031)	-2.139*** (0.510)
as.factor(market)93	-3.863*** (1.152)	-6.450*** (1.317)	-1.703 (0.935)	-0.985* (0.498)

Table 9: (continued)

	<i>Dependent variable:</i>			
	UR 2016 (1)	UR 2021 (2)	Yabloko 2016 (3)	Yabloko 2021 (4)
as.factor(market)94	-9.686*** (1.451)	-9.315*** (1.632)	-9.847*** (1.264)	-3.154*** (0.627)
as.factor(market)95	-2.252* (1.046)	-5.457*** (1.187)	-2.252** (0.865)	-0.468 (0.452)
as.factor(market)96	-4.270*** (1.079)	-3.919** (1.228)	-3.281*** (0.905)	-0.622 (0.466)
as.factor(market)97	1.395 (1.730)	0.831 (2.009)	-5.078*** (1.409)	-0.929 (0.747)
as.factor(market)98	-14.633 (16.308)	-1.971 (18.620)	4.373 (12.725)	-11.618 (7.059)
as.factor(market)99	-15.901*** (2.962)	-15.057*** (3.437)	-11.804*** (2.274)	-3.564** (1.282)
proximity:pop_hund	0.218*** (0.019)	0.299*** (0.021)	0.008 (0.021)	0.065*** (0.008)
Observations	31,439	33,564	24,539	31,998
R <sup>2</sup>	0.052	0.046	0.082	0.029
Adjusted R <sup>2</sup>	-0.107	-0.110	-0.091	-0.139

Note:

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

## **C Robustness checks**

Figure 7: Robustness check: effect of geographical proximity on turnout at federal parliamentary and presidential elections

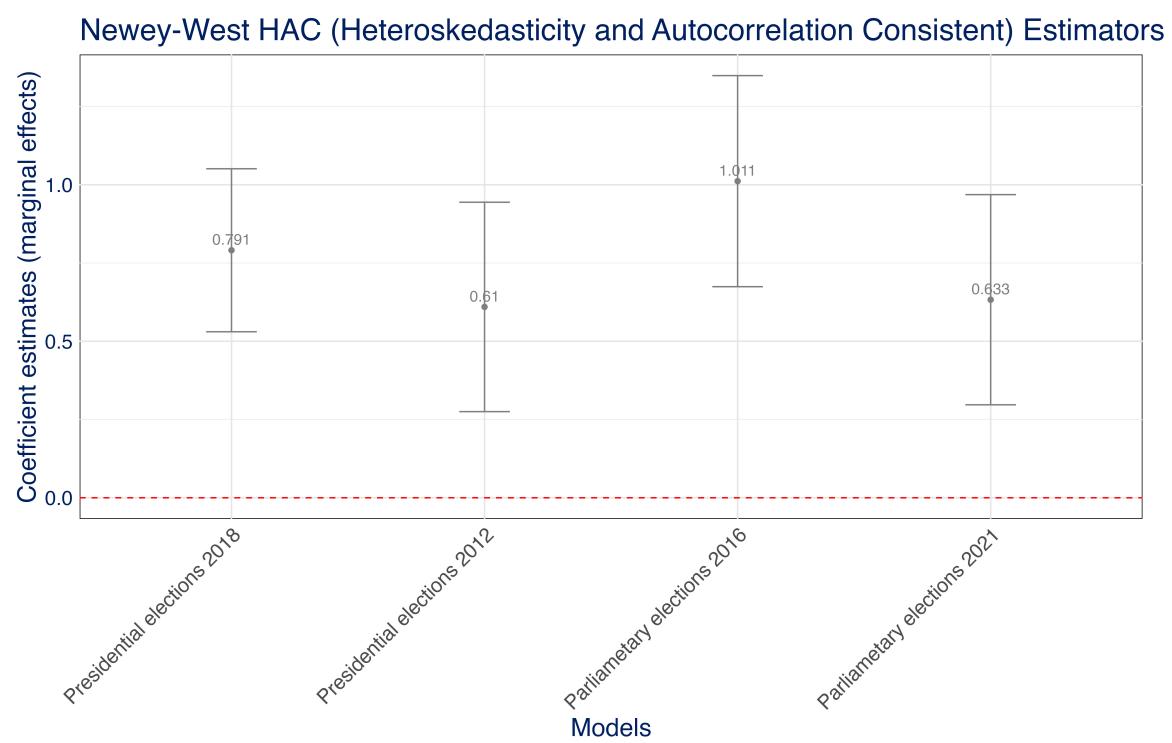


Figure 8: Robustness check: effect of geographical proximity on vote shares at federal parliamentary elections

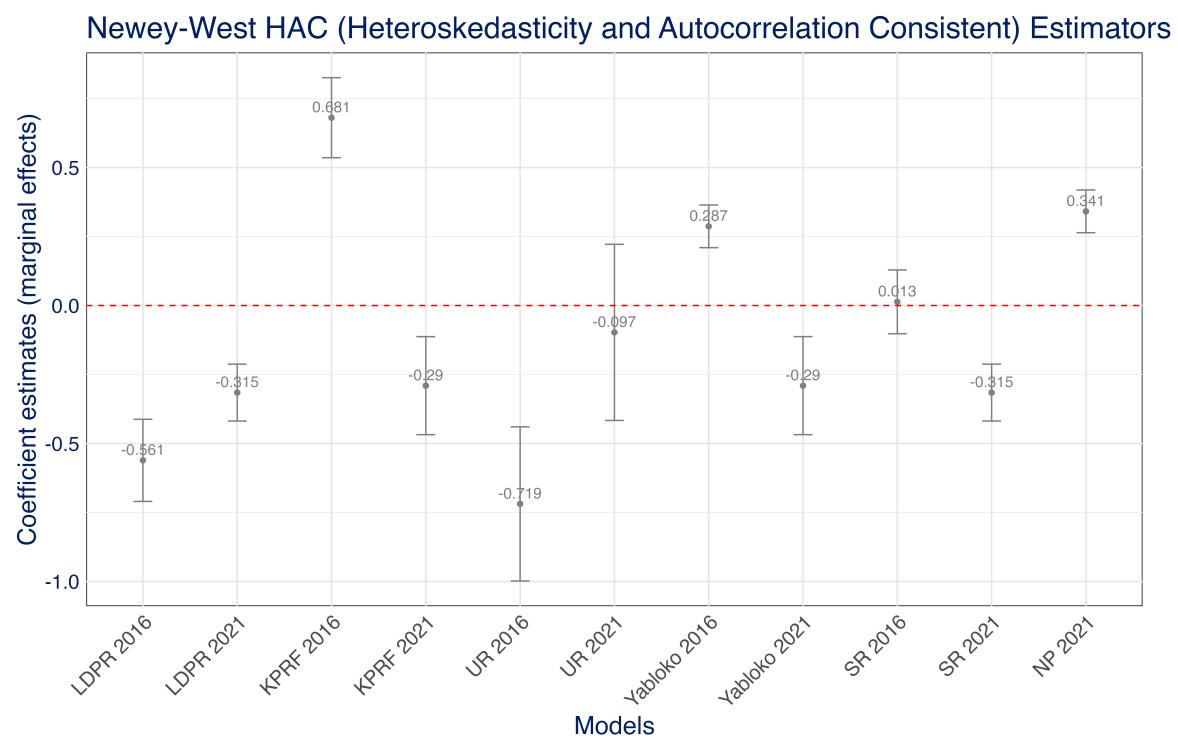


Figure 9: Robustness check: effect of geographical proximity on vote shares at presidential elections

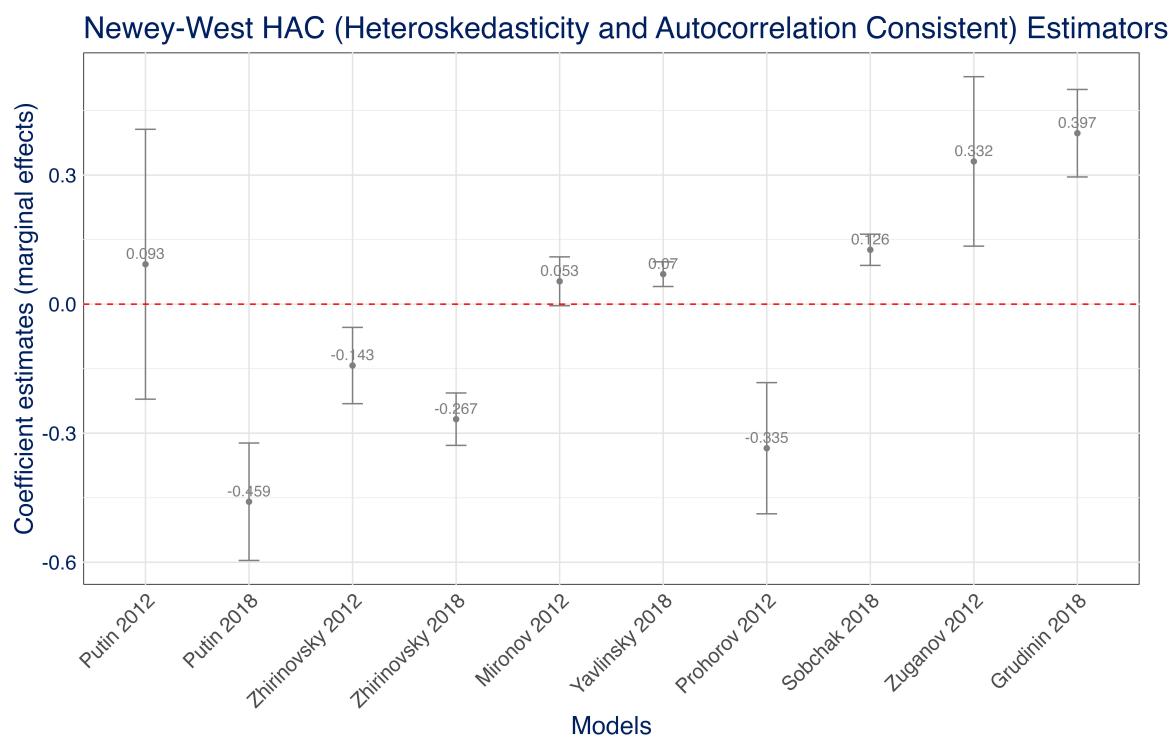
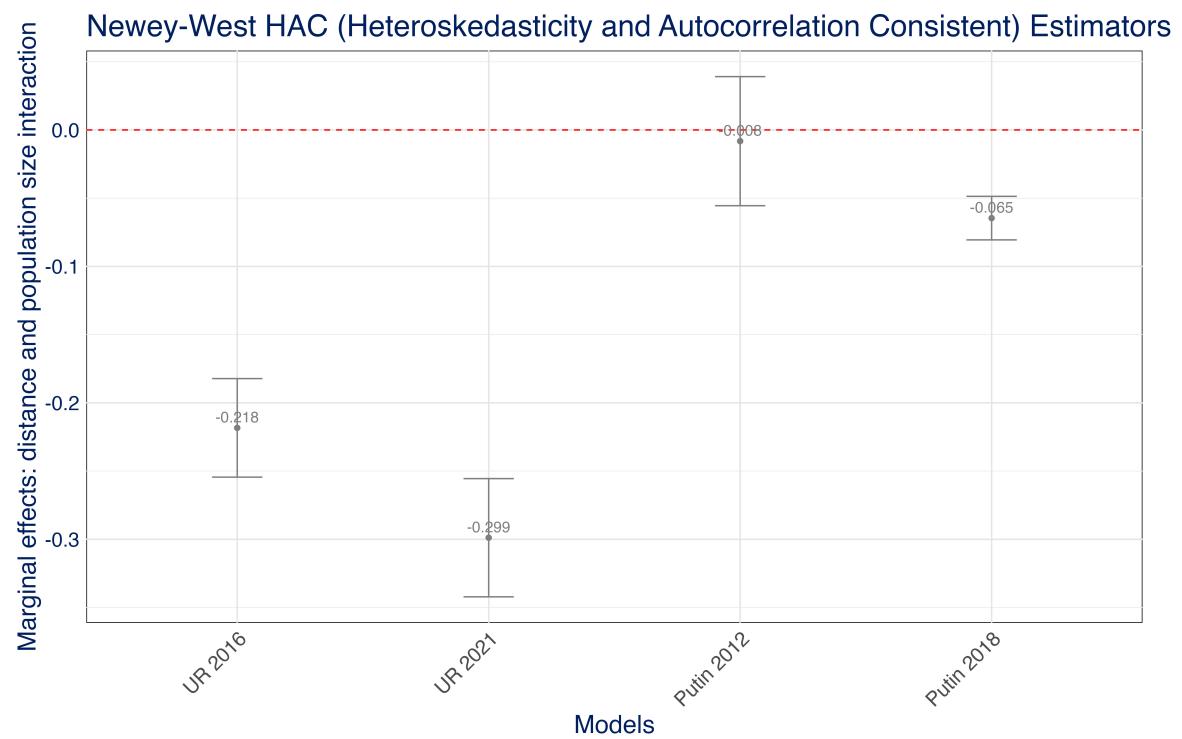


Figure 10: Robustness check: effect of geographical proximity and electoral committee size interaction on vote shares at parliamentary and presidential elections



## D Robustness checks regression tables

Table 10: Newey-West HAC (Heteroskedasticity and Autocorrelation Consistent) Estimators

Model	Coefficient	SE
LDPR 2016	-0.56	0.08
LDPR 2021	-0.32	0.05
KPRF 2016	0.68	0.07
KPRF 2021	-0.29	0.09
UR 2016	-0.72	0.14
UR 2021	-0.10	0.16
Yabloko 2016	0.29	0.04
Yabloko 2021	-0.29	0.09
SR 2016	0.01	0.06
SR 2021	-0.32	0.05
NP 2021	0.34	0.04

Table 11: Newey-West HAC (Heteroskedasticity and Autocorrelation Consistent) Estimators

Model	Coefficient	SE
Putin 2012	0.09	0.16
Putin 2018	-0.46	0.07
Zhirinovsky 2012	-0.14	0.05
Zhirinovsky 2018	-0.27	0.03
Mironov 2012	0.05	0.03
Yavlinsky 2018	0.07	0.01
Prohorov 2012	-0.33	0.08
Sobchak 2018	0.13	0.02
Zuganov 2012	0.33	0.10
Grudinin 2018	0.40	0.05

Table 12: Newey-West HAC (Heteroskedasticity and Autocorrelation Consistent) Estimators

Model	Coefficient	SE
Presidential elections 2018	0.79	0.13
Presidential elections 2012	0.61	0.17
Parliamentary elections 2016	1.01	0.17
Parliamentary elections 2021	0.63	0.17

## **E Robustness checks: salary test for turnout**

Figure 11: Regression results: effect of geographical proximity on turnout at 2012 presidential elections (market and region FE included)

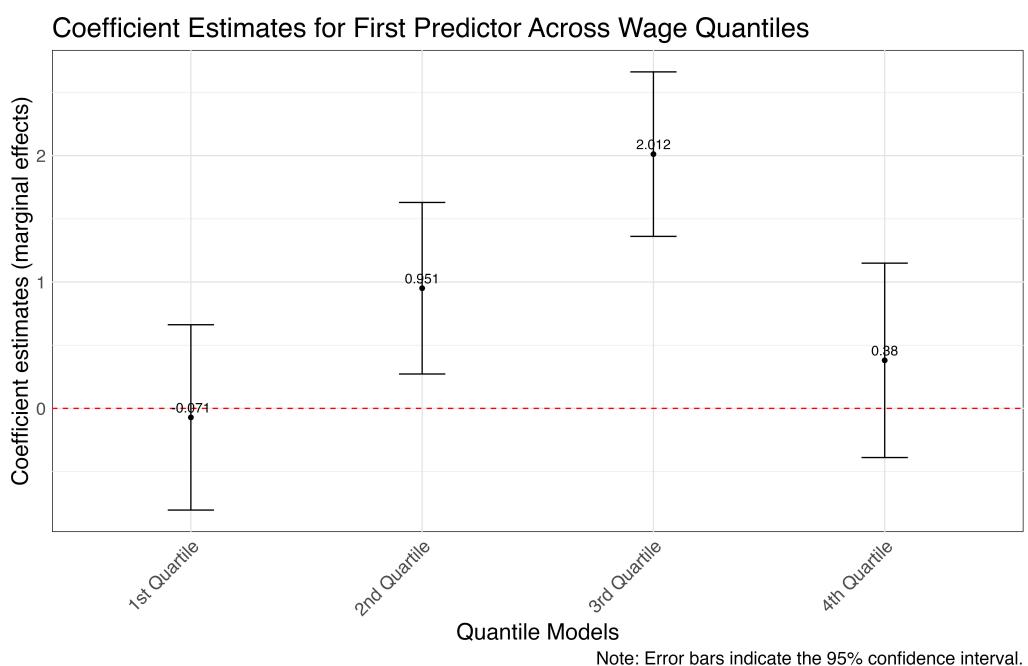


Figure 12: Regression results: effect of geographical proximity on turnout at 2016 federal parliamentary elections (market and region FE included)

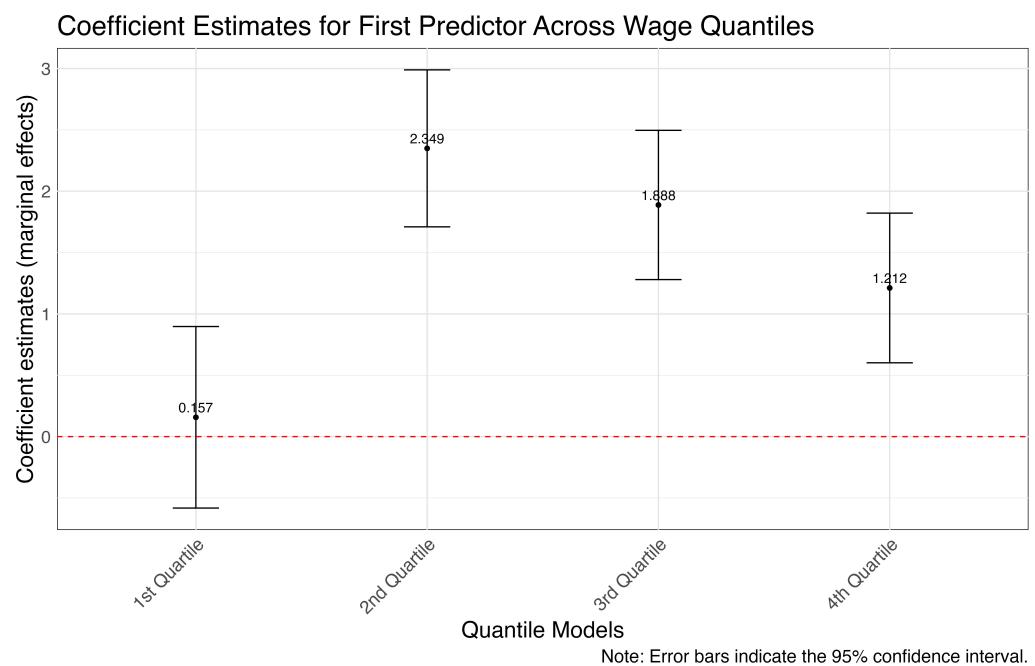
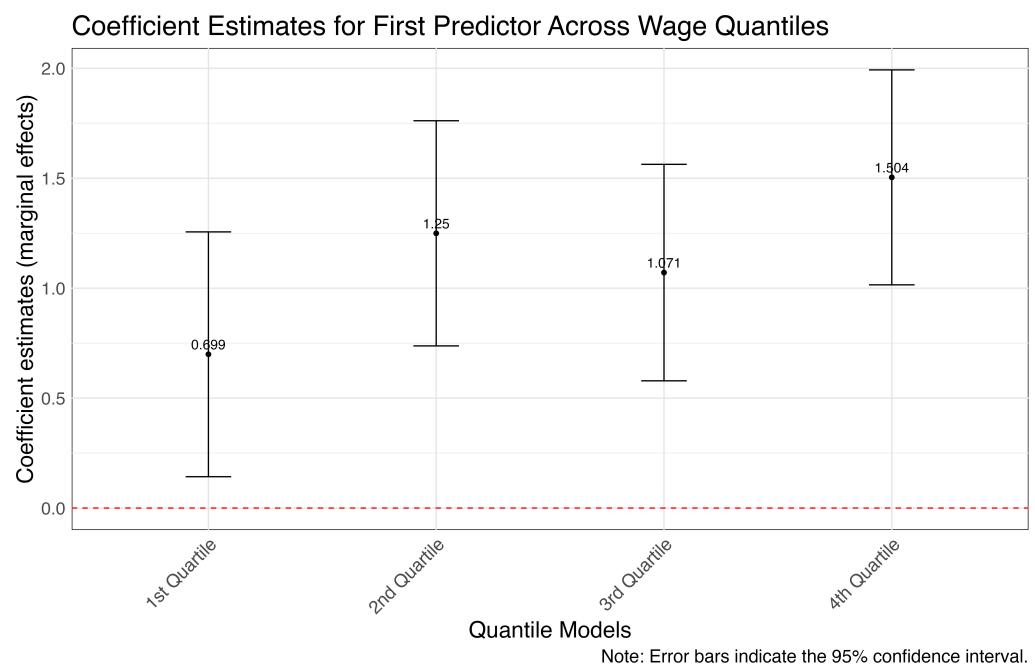


Figure 13: Regression results: effect of geographical proximity on turnout at 2018 presidential elections (market and region FE included)



## F Robustness checks: salary test for turnout. Regression Tables

Table 13: Regression results by wage quartiles: effect of geographical proximity on turnout at 2012 presidential elections (market and region FE included)

	<i>Dependent variable:</i>			
	Wage 1st quar (1)	Wage 2nd quar (2)	Wage 3rd quar (3)	Wage 4th quar (4)
proximity	0.699* (0.284)	1.250*** (0.261)	1.071*** (0.251)	1.504*** (0.249)
as.factor(market)02	0.018 (1.058)	-1.879 (1.135)	1.727 (1.001)	2.238* (1.136)
as.factor(market)03	-1.126 (1.103)	-1.444 (1.042)	-0.022 (1.002)	1.389 (1.208)
as.factor(market)05	-1.654 (1.998)	3.998 (2.579)	0.546 (1.337)	4.095** (1.504)
as.factor(market)06	0.088 (3.310)	-2.996 (1.575)	-1.838 (1.703)	1.290 (1.593)
as.factor(market)07	-1.343 (1.935)	-1.527 (1.731)	0.882 (1.495)	1.873 (1.347)
as.factor(market)08	-0.487 (1.002)	-0.229 (0.997)	0.024 (1.180)	1.829 (1.190)
as.factor(market)09	-0.318 (1.638)	-0.943 (1.099)	-1.991 (1.386)	-0.709 (1.234)
as.factor(market)10	-1.129 (0.927)	-2.116* (0.994)	-0.874 (1.111)	1.736 (1.242)
as.factor(market)11	-2.424* (1.005)	0.771 (0.958)	0.763 (1.072)	0.504 (1.222)
as.factor(market)12	-2.414	2.224	-0.569	0.708

Table 13: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)13	(2.178) −0.549 (1.054)	(1.439) 0.095 (0.971)	(1.388) 0.961 (1.152)	(1.343) 0.365 (1.177)
as.factor(market)14	−0.036 (1.044)	−1.413 (0.993)	0.686 (1.072)	1.205 (1.156)
as.factor(market)15	−0.194 (1.146)	−1.960 (1.068)	−0.730 (1.111)	3.977*** (1.160)
as.factor(market)16	−0.579 (1.094)	−0.833 (1.024)	−0.212 (1.104)	2.696* (1.188)
as.factor(market)17	0.428 (1.158)	−3.346** (1.024)	−0.127 (1.020)	1.644 (1.119)
as.factor(market)18	−0.500 (1.029)	−1.425 (1.005)	−0.291 (1.038)	2.137 (1.093)
as.factor(market)19	−1.937 (1.719)	−1.882 (1.475)	−0.596 (1.238)	2.747* (1.323)
as.factor(market)20	−0.678 (1.048)	0.300 (1.066)	−0.217 (1.068)	1.861 (1.170)
as.factor(market)21	−0.953 (1.119)	−1.495 (1.191)	−0.272 (1.294)	1.634 (1.346)
as.factor(market)22	−0.373 (1.009)	−1.708 (1.078)	2.581* (1.158)	−0.210 (1.214)
as.factor(market)23	0.108 (1.043)	−1.654 (1.062)	0.429 (1.136)	1.680 (1.317)
as.factor(market)24	−1.365 (1.161)	−2.264* (1.132)	0.243 (1.057)	1.835 (1.170)
as.factor(market)25	−3.045** −3.045**	0.578	−1.397	0.555

Table 13: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)26	(1.148) -1.674 (1.065)	(1.151) 0.018 (1.040)	(1.344) -1.208 (1.172)	(1.362) 0.434 (1.183)
as.factor(market)27	-0.371 (1.144)	0.769 (1.058)	0.743 (1.165)	2.306 (1.204)
as.factor(market)28	-0.875 (1.075)	0.129 (1.030)	-1.121 (1.120)	0.949 (1.246)
as.factor(market)29	-2.080 (1.236)	-0.993 (1.128)	-1.555 (1.154)	1.614 (1.195)
as.factor(market)30	-0.341 (1.139)	-0.334 (1.200)	-1.284 (1.073)	2.923* (1.217)
as.factor(market)31	-0.355 (1.152)	-1.179 (1.234)	-0.723 (1.095)	3.078** (1.173)
as.factor(market)32	-0.053 (1.008)	-0.552 (0.978)	-0.532 (1.196)	1.965 (1.161)
as.factor(market)33	-1.478 (1.059)	-0.394 (0.999)	-0.870 (1.246)	2.502* (1.130)
as.factor(market)35	-0.489 (1.024)	-0.825 (0.965)	-0.162 (1.042)	1.651 (1.192)
as.factor(market)36	0.005 (1.152)	-0.117 (1.088)	-0.128 (1.080)	0.609 (1.113)
as.factor(market)37	0.211 (1.198)	-1.286 (1.034)	-1.078 (1.185)	0.965 (1.070)
as.factor(market)38	-1.327 (1.039)	1.121 (1.054)	-0.573 (1.132)	0.889 (1.225)
as.factor(market)39		0.380	-2.013	-0.837

Table 13: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)41	0.888 (1.051)	-0.699 (1.230)	-0.640 (1.818)	-0.147 (2.436)
as.factor(market)42	0.696 (1.039)	-1.391 (1.126)	-0.382 (1.249)	2.018 (1.205)
as.factor(market)43	-0.051 (0.998)	-0.779 (1.091)	0.779 (1.724)	2.312 (1.863)
as.factor(market)45	-2.235 (1.155)	-0.945 (1.121)	-0.758 (1.183)	2.486 (1.591)
as.factor(market)46	-0.436 (0.960)	0.659 (1.470)	-5.150* (2.581)	0.917 (1.917)
as.factor(market)47	-2.524* (1.155)	-0.955 (1.435)	0.443 (1.912)	0.579 (2.694)
as.factor(market)49	-2.115* (1.068)	0.327 (1.217)	-0.792 (1.541)	-0.048 (1.698)
as.factor(market)50	-4.259 (2.224)	-3.023* (1.252)	0.863 (1.343)	1.922 (1.195)
as.factor(market)51	-1.851 (1.873)	1.434 (1.324)	0.810 (1.217)	0.669 (1.155)
as.factor(market)52	0.767 (1.034)	0.173 (1.137)	0.128 (1.268)	3.295* (1.547)
as.factor(market)53	-0.262 (1.039)	-0.469 (0.998)	0.541 (1.053)	2.363* (1.172)
as.factor(market)55	-1.941 (1.048)	-0.569 (1.017)	0.069 (1.301)	0.857 (1.104)
as.factor(market)56	-1.574	0.860	0.119	0.154

Table 13: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)58	(1.032) 0.676 (1.151)	(1.186) −0.743 (1.030)	(1.409) −0.053 (1.102)	(1.563) 1.518 (1.137)
as.factor(market)59	−0.172 (1.238)	0.795 (1.083)	1.618 (1.174)	1.775 (1.125)
as.factor(market)60	2.105 (1.144)	−0.383 (0.978)	0.493 (1.013)	2.899** (1.089)
as.factor(market)61	−0.498 (0.990)	−0.212 (0.993)	0.549 (0.991)	2.487* (1.101)
as.factor(market)62	−0.308 (1.110)	−0.522 (1.265)	2.449* (1.226)	1.769 (1.387)
as.factor(market)63	−1.154 (1.073)	1.260 (1.055)	−0.748 (1.151)	3.130* (1.306)
as.factor(market)64	−1.780 (1.103)	1.124 (1.038)	1.923 (1.260)	1.013 (1.167)
as.factor(market)65	−4.755*** (1.420)	1.301 (1.454)	−1.747 (1.830)	0.179 (1.588)
as.factor(market)66	−0.642 (1.076)	0.859 (0.986)	2.511* (1.137)	1.208 (1.211)
as.factor(market)68	−0.005 (1.085)	−1.123 (1.261)	−0.391 (1.820)	5.826** (1.917)
as.factor(market)69	−2.330* (1.141)	0.846 (1.242)	0.511 (1.225)	3.762* (1.598)
as.factor(market)70	−0.807 (1.136)	0.611 (1.035)	−0.042 (1.172)	1.416 (1.537)
as.factor(market)71	−1.223	0.186	−0.254	0.477

Table 13: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)72	(1.087) 0.927 (1.229)	(1.157) 0.474 (1.093)	(1.280) −1.083 (1.302)	(1.376) 1.241 (1.479)
as.factor(market)73	−0.385 (1.065)	−0.756 (1.137)	1.677 (1.239)	3.467** (1.312)
as.factor(market)74	−0.245 (1.102)	−1.279 (1.078)	1.130 (1.165)	0.465 (1.237)
as.factor(market)75	−1.740 (1.102)	−1.209 (1.006)	2.171* (1.079)	1.648 (1.219)
as.factor(market)77	0.200 (1.173)	−1.153 (1.311)	1.628 (1.263)	2.886* (1.384)
as.factor(market)78	−1.076 (1.412)	−1.501 (1.116)	0.317 (1.254)	0.187 (1.260)
as.factor(market)79	0.607 (1.250)	−0.664 (1.132)	2.300 (1.264)	2.076 (1.405)
as.factor(market)80	−1.188 (1.075)	−1.647 (1.086)	0.631 (1.184)	1.583 (1.328)
as.factor(market)81	0.027 (1.029)	−0.020 (0.983)	0.347 (1.200)	1.487 (1.252)
as.factor(market)82	−0.898 (1.116)	−2.030 (1.133)	2.167 (1.271)	2.046 (1.253)
as.factor(market)84	−1.382 (1.188)	−1.292 (1.097)	−0.301 (1.020)	1.505 (1.116)
as.factor(market)85	0.087 (1.089)	−1.039 (0.982)	−1.214 (1.200)	2.047 (1.155)
as.factor(market)86	−0.684	−0.757	1.455	2.750*

Table 13: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)87	(0.969) -1.315 (1.405)	(1.089) 0.155 (1.141)	(1.170) 0.624 (1.090)	(1.234) 2.076 (1.247)
as.factor(market)88	0.205 (1.133)	-0.245 (1.156)	1.370 (1.094)	2.611* (1.156)
as.factor(market)90	-0.288 (1.061)	0.593 (1.103)	0.987 (1.386)	4.304*** (1.168)
as.factor(market)91	-0.908 (1.463)	-3.115* (1.216)	-1.159 (1.275)	0.509 (1.221)
as.factor(market)92	-2.269 (2.598)	-0.291 (1.332)	1.923 (1.533)	2.414 (1.340)
as.factor(market)93	0.533 (0.989)	1.847 (1.133)	1.405 (1.351)	2.934* (1.297)
as.factor(market)94	-1.807 (2.020)	-2.360 (1.387)	1.357 (1.547)	2.287 (1.348)
as.factor(market)95	-0.894 (1.062)	-0.886 (0.983)	1.626 (1.081)	-0.231 (1.191)
as.factor(market)96	-1.265 (1.042)	0.912 (1.008)	1.563 (1.241)	0.426 (1.259)
as.factor(market)97	-3.575 (3.305)	3.089 (3.808)	0.659 (1.455)	3.510* (1.478)
as.factor(market)98		0.151 (6.869)		
as.factor(market)99				9.826 (5.504)
uik_population	-0.002***	-0.002***	-0.001***	-0.002***

Table 13: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Observations	7,998	7,127	7,011	8,008
R <sup>2</sup>	0.041	0.048	0.031	0.050
Adjusted R <sup>2</sup>	-0.020	-0.015	-0.030	-0.005
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001			

Table 14: Regression results by wage quartiles: effect of geographical proximity on turnout at 2016 parliamentary elections (market and region FE included)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
proximity	0.157 (0.377)	2.349*** (0.326)	1.888*** (0.310)	1.212*** (0.311)
as.factor(market)02	1.805 (1.450)	0.777 (1.376)	2.814* (1.225)	0.757 (1.405)
as.factor(market)03	-0.674 (1.408)	-1.102 (1.342)	1.399 (1.230)	2.469 (1.487)
as.factor(market)05	1.616 (2.625)	7.390* (3.251)	1.776 (1.644)	5.153** (1.823)
as.factor(market)06	2.229	-1.787	1.008	0.123

Table 14: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)07	(4.343) 1.332 (3.280)	(2.018) −1.671 (1.930)	(2.057) 2.959 (1.838)	(1.969) 0.014 (1.714)
as.factor(market)08	−0.639 (1.315)	−0.343 (1.271)	0.488 (1.406)	1.243 (1.460)
as.factor(market)09	1.431 (2.091)	−1.073 (1.391)	−1.587 (1.720)	−0.633 (1.535)
as.factor(market)10	−0.723 (1.213)	−1.928 (1.295)	1.106 (1.405)	1.380 (1.501)
as.factor(market)11	−1.411 (1.304)	1.847 (1.207)	0.419 (1.319)	−0.415 (1.489)
as.factor(market)12	−0.207 (2.857)	4.454* (1.809)	−0.657 (1.706)	4.777** (1.666)
as.factor(market)13	−0.110 (1.368)	0.380 (1.233)	1.894 (1.389)	−0.301 (1.446)
as.factor(market)14	−0.966 (1.370)	−0.669 (1.254)	1.779 (1.300)	−0.215 (1.429)
as.factor(market)15	−3.230* (1.546)	−0.231 (1.314)	0.235 (1.383)	2.807 (1.464)
as.factor(market)16	−1.241 (1.435)	1.302 (1.293)	0.531 (1.349)	1.655 (1.456)
as.factor(market)17	−3.283* (1.583)	−2.423 (1.280)	1.331 (1.256)	−0.066 (1.371)
as.factor(market)18	0.375 (1.366)	−0.557 (1.255)	1.135 (1.272)	0.927 (1.334)
as.factor(market)19	−1.832	0.731	2.315	2.142

Table 14: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)20	(2.282) −2.025 (1.398)	(1.881) 3.775** (1.335)	(1.535) 0.754 (1.301)	(1.612) 3.181* (1.433)
as.factor(market)21	−1.278 (1.498)	−1.581 (1.486)	−0.690 (1.600)	1.187 (1.646)
as.factor(market)22	−1.960 (1.321)	−0.014 (1.372)	1.603 (1.413)	0.271 (1.478)
as.factor(market)23	0.685 (1.376)	−1.191 (1.291)	2.681 (1.395)	1.278 (1.603)
as.factor(market)24	−1.531 (1.533)	−0.099 (1.449)	−1.012 (1.295)	1.765 (1.454)
as.factor(market)25	−0.047 (1.498)	1.482 (1.532)	1.264 (1.605)	−0.315 (1.649)
as.factor(market)26	−1.200 (1.371)	−0.103 (1.322)	−0.209 (1.430)	−0.177 (1.472)
as.factor(market)27	0.351 (1.465)	1.011 (1.363)	0.277 (1.449)	0.875 (1.475)
as.factor(market)28	−0.327 (1.409)	1.183 (1.307)	0.195 (1.373)	1.426 (1.514)
as.factor(market)29	−0.385 (1.591)	−1.487 (1.439)	3.291* (1.442)	0.376 (1.497)
as.factor(market)30	−2.345 (1.510)	3.336* (1.480)	−0.830 (1.348)	1.047 (1.524)
as.factor(market)31	0.508 (1.533)	−0.366 (1.562)	2.026 (1.333)	1.986 (1.430)
as.factor(market)32	−0.727	0.089	0.070	0.218

Table 14: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)33	(1.286) −1.420 (1.383)	(1.256) −0.512 (1.265)	(1.464) 0.622 (1.513)	(1.408) 2.721* (1.376)
as.factor(market)35	−1.092 (1.350)	−0.411 (1.205)	0.585 (1.266)	−0.158 (1.457)
as.factor(market)36	−0.738 (1.514)	0.062 (1.382)	2.041 (1.323)	1.800 (1.359)
as.factor(market)37	0.281 (1.585)	−0.274 (1.294)	1.619 (1.477)	0.673 (1.312)
as.factor(market)38	−2.572 (1.371)	0.982 (1.334)	0.550 (1.373)	0.994 (1.484)
as.factor(market)39		−1.127 (2.077)	2.142 (1.926)	0.222 (2.081)
as.factor(market)41	1.122 (1.382)	−1.797 (1.657)	2.458 (2.005)	0.330 (2.948)
as.factor(market)42	1.325 (1.354)	0.222 (1.455)	−0.733 (1.510)	1.693 (1.484)
as.factor(market)43	−1.384 (1.299)	−1.175 (1.408)	3.722 (2.015)	3.076 (2.331)
as.factor(market)45	−1.480 (1.517)	−1.565 (1.452)	1.238 (1.418)	0.616 (1.926)
as.factor(market)46	−1.203 (1.263)	−1.731 (2.168)	7.866** (2.506)	2.229 (2.320)
as.factor(market)47	−2.099 (1.510)	−1.282 (1.879)	3.270 (2.243)	−0.156 (3.261)
as.factor(market)49	−4.104**	0.736	0.249	−0.261

Table 14: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)50	(1.408) −0.246 (2.823)	(1.559) −1.110 (1.583)	(1.807) 0.919 (1.677)	(2.031) 1.568 (1.464)
as.factor(market)51	−1.212 (2.106)	1.888 (1.647)	0.629 (1.496)	0.860 (1.425)
as.factor(market)52	−0.743 (1.361)	0.507 (1.430)	1.508 (1.564)	1.835 (1.873)
as.factor(market)53	−0.236 (1.359)	−1.136 (1.266)	0.857 (1.292)	1.638 (1.433)
as.factor(market)55	−2.728* (1.357)	−0.348 (1.311)	0.822 (1.531)	0.246 (1.363)
as.factor(market)56	0.069 (1.375)	0.381 (1.473)	2.847 (1.702)	1.004 (1.892)
as.factor(market)58	−0.810 (1.508)	−0.063 (1.296)	0.115 (1.352)	1.250 (1.395)
as.factor(market)59	−2.311 (1.627)	1.425 (1.373)	0.549 (1.421)	1.999 (1.377)
as.factor(market)60	1.955 (1.525)	0.900 (1.224)	2.686* (1.238)	1.508 (1.333)
as.factor(market)61	−1.177 (1.304)	0.243 (1.249)	3.127* (1.214)	1.501 (1.344)
as.factor(market)62	−0.955 (1.456)	2.550 (1.620)	4.464** (1.501)	2.253 (1.680)
as.factor(market)63	−1.041 (1.403)	0.673 (1.344)	−0.165 (1.401)	2.093 (1.611)
as.factor(market)64	−1.750	0.429	3.508*	1.626

Table 14: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)65	(1.457) -4.331*	(1.297) 3.929*	(1.579) -0.107	(1.440) 2.917
as.factor(market)66	(1.826) -0.641	(1.827) 2.698*	(2.252) 3.648**	(1.968) 0.693
as.factor(market)68	(1.371) 0.642	(1.261) 0.783	(1.388) -0.725	(1.495) 2.946
as.factor(market)69	(1.418) -0.171	(1.716) -0.095	(1.987) 2.203	(2.322) 3.316
as.factor(market)70	(1.497) -1.189	(1.603) 4.016**	(1.479) 2.749	(1.954) 2.136
as.factor(market)71	(1.365) -0.885	(1.342) 1.258	(1.435) 2.149	(1.860) 0.008
as.factor(market)72	(1.432) 0.368	(1.476) 1.903	(1.537) 2.160	(1.670) -0.433
as.factor(market)73	(1.557) 0.044	(1.373) -0.328	(1.582) 2.422	(1.791) 0.972
as.factor(market)74	(1.401) 1.279	(1.430) -1.840	(1.524) 2.630	(1.619) -1.725
as.factor(market)75	(1.378) -0.682	(1.304) -0.204	(1.333) 2.824*	(1.503) 1.447
as.factor(market)77	(1.613) 0.596	(1.622) 0.653	(1.525) 2.820	(1.675) 2.240
as.factor(market)78	(1.795) -0.410	(1.419) -0.443	(1.542) 0.461	(1.554) 0.581
as.factor(market)79	-0.205	0.738	3.941*	3.156

Table 14: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)80	(1.608) −0.290 (1.392)	(1.443) −2.555 (1.431)	(1.555) 0.823 (1.410)	(1.701) 0.979 (1.624)
as.factor(market)81	−0.973 (1.357)	−0.492 (1.248)	4.060** (1.427)	2.230 (1.523)
as.factor(market)82	−1.051 (1.494)	−0.417 (1.390)	3.154* (1.553)	−0.155 (1.560)
as.factor(market)84	−0.462 (1.497)	−0.063 (1.431)	2.069 (1.286)	0.193 (1.376)
as.factor(market)85	−0.478 (1.407)	0.016 (1.255)	1.258 (1.431)	1.468 (1.402)
as.factor(market)86	0.370 (1.274)	1.393 (1.379)	3.241* (1.422)	1.732 (1.508)
as.factor(market)87	−1.700 (1.790)	−0.392 (1.457)	2.544 (1.339)	1.633 (1.538)
as.factor(market)88	0.890 (1.466)	−0.629 (1.494)	0.566 (1.351)	1.756 (1.418)
as.factor(market)90	−0.683 (1.402)	0.847 (1.412)	2.874 (1.638)	4.842*** (1.438)
as.factor(market)91	−0.492 (2.039)	−1.820 (1.487)	−0.053 (1.568)	−0.577 (1.496)
as.factor(market)92	−1.535 (3.382)	−1.064 (1.734)	4.015* (1.885)	1.533 (1.652)
as.factor(market)93	−0.590 (1.320)	3.487* (1.434)	2.428 (1.572)	3.133* (1.579)
as.factor(market)94	−1.803	−1.059	1.826	3.127

Table 14: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)95	(2.966) -0.819 (1.369)	(1.706) 0.623 (1.274)	(1.863) 2.760* (1.279)	(1.636) -0.018 (1.450)
as.factor(market)96	-1.199 (1.382)	1.185 (1.283)	1.563 (1.469)	-0.771 (1.536)
as.factor(market)97	-1.421 (4.679)	0.618 (4.256)	-0.093 (1.788)	1.929 (1.807)
as.factor(market)98		3.489 (8.667)		
as.factor(market)99				9.934 (6.662)
uik_population	-0.002*** (0.0002)	-0.003*** (0.0002)	-0.002*** (0.0002)	-0.003*** (0.0002)
Observations	8,000	6,823	7,169	7,610
R <sup>2</sup>	0.034	0.071	0.038	0.074
Adjusted R <sup>2</sup>	-0.026	0.010	-0.023	0.018
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001			

Table 15: Regression results by wage quartiles: effect of geographical proximity on turnout at 2018 presidential elections (market and region FE included)

	<i>Dependent variable:</i>			
	Wage 1st quar (1)	Wage 2nd quar (2)	Wage 3rd quar (3)	Wage 4th quar (4)
proximity	0.699* (0.284)	1.250*** (0.261)	1.071*** (0.251)	1.504*** (0.249)
as.factor(market)02	0.018 (1.058)	-1.879 (1.135)	1.727 (1.001)	2.238* (1.136)
as.factor(market)03	-1.126 (1.103)	-1.444 (1.042)	-0.022 (1.002)	1.389 (1.208)
as.factor(market)05	-1.654 (1.998)	3.998 (2.579)	0.546 (1.337)	4.095** (1.504)
as.factor(market)06	0.088 (3.310)	-2.996 (1.575)	-1.838 (1.703)	1.290 (1.593)
as.factor(market)07	-1.343 (1.935)	-1.527 (1.731)	0.882 (1.495)	1.873 (1.347)
as.factor(market)08	-0.487 (1.002)	-0.229 (0.997)	0.024 (1.180)	1.829 (1.190)
as.factor(market)09	-0.318 (1.638)	-0.943 (1.099)	-1.991 (1.386)	-0.709 (1.234)
as.factor(market)10	-1.129 (0.927)	-2.116* (0.994)	-0.874 (1.111)	1.736 (1.242)
as.factor(market)11	-2.424* (1.005)	0.771 (0.958)	0.763 (1.072)	0.504 (1.222)
as.factor(market)12	-2.414 (2.178)	2.224 (1.439)	-0.569 (1.388)	0.708 (1.343)
as.factor(market)13	-0.549	0.095	0.961	0.365

Table 15: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)14	(1.054) −0.036	(0.971) −1.413	(1.152) 0.686	(1.177) 1.205
as.factor(market)15	(1.044) −0.194	(0.993) −1.960	(1.072) −0.730	(1.156) 3.977***
as.factor(market)16	(1.146) −0.579	(1.068) −0.833	(1.111) −0.212	(1.160) 2.696*
as.factor(market)17	(1.094) 0.428	(1.024) −3.346**	(1.104) −0.127	(1.188) 1.644
as.factor(market)18	(1.158) −0.500	(1.024) −1.425	(1.020) −0.291	(1.119) 2.137
as.factor(market)19	(1.719) −1.937	(1.475) −1.882	(1.238) −0.596	(1.323) 2.747*
as.factor(market)20	(1.029) −0.678	(1.005) 0.300	(1.038) −0.217	(1.093) 1.861
as.factor(market)21	(1.119) −0.953	(1.191) −1.495	(1.294) −0.272	(1.346) 1.634
as.factor(market)22	(1.009) −0.373	(1.078) −1.708	(1.158) 2.581*	(1.214) −0.210
as.factor(market)23	(1.043) 0.108	(1.062) −1.654	(1.136) 0.429	(1.317) 1.680
as.factor(market)24	(1.161) −1.365	(1.132) −2.264*	(1.057) 0.243	(1.170) 1.835
as.factor(market)25	−3.045** (1.148)	0.578 (1.151)	−1.397 (1.344)	0.555 (1.362)
as.factor(market)26	−1.674	0.018	−1.208	0.434

Table 15: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)27	(1.065) -0.371 (1.144)	(1.040) 0.769 (1.058)	(1.172) 0.743 (1.165)	(1.183) 2.306 (1.204)
as.factor(market)28	-0.875 (1.075)	0.129 (1.030)	-1.121 (1.120)	0.949 (1.246)
as.factor(market)29	-2.080 (1.236)	-0.993 (1.128)	-1.555 (1.154)	1.614 (1.195)
as.factor(market)30	-0.341 (1.139)	-0.334 (1.200)	-1.284 (1.073)	2.923* (1.217)
as.factor(market)31	-0.355 (1.152)	-1.179 (1.234)	-0.723 (1.095)	3.078** (1.173)
as.factor(market)32	-0.053 (1.008)	-0.552 (0.978)	-0.532 (1.196)	1.965 (1.161)
as.factor(market)33	-1.478 (1.059)	-0.394 (0.999)	-0.870 (1.246)	2.502* (1.130)
as.factor(market)35	-0.489 (1.024)	-0.825 (0.965)	-0.162 (1.042)	1.651 (1.192)
as.factor(market)36	0.005 (1.152)	-0.117 (1.088)	-0.128 (1.080)	0.609 (1.113)
as.factor(market)37	0.211 (1.198)	-1.286 (1.034)	-1.078 (1.185)	0.965 (1.070)
as.factor(market)38	-1.327 (1.039)	1.121 (1.054)	-0.573 (1.132)	0.889 (1.225)
as.factor(market)39		0.380 (1.652)	-2.013 (1.593)	-0.837 (1.719)
as.factor(market)41	0.888	-0.699	-0.640	-0.147

Table 15: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)42	(1.051) 0.696	(1.230) −1.391	(1.818) −0.382	(2.436) 2.018
as.factor(market)43	(1.039) −0.051	(1.126) −0.779	(1.249) 0.779	(1.205) 2.312
as.factor(market)45	(0.998) −2.235	(1.091) −0.945	(1.724) −0.758	(1.863) 2.486
as.factor(market)46	(1.155) −0.436	(1.121) 0.659	(1.183) −5.150*	(1.591) 0.917
as.factor(market)47	(0.960) −2.524*	(1.470) −0.955	(2.581) 0.443	(1.917) 0.579
as.factor(market)49	(1.068) −2.115*	(1.217) 0.327	(1.541) −0.792	(1.698) −0.048
as.factor(market)50	(2.224) −4.259	(1.252) −3.023*	(1.343) 0.863	(1.195) 1.922
as.factor(market)51	(1.873) −1.851	(1.324) 1.434	(1.217) 0.810	(1.155) 0.669
as.factor(market)52	(1.034) 0.767	(1.137) 0.173	(1.268) 0.128	(1.547) 3.295*
as.factor(market)53	(1.039) −0.262	(0.998) −0.469	(1.053) 0.541	(1.172) 2.363*
as.factor(market)55	(1.048) −1.941	(1.017) −0.569	(1.301) 0.069	(1.104) 0.857
as.factor(market)56	(1.032) −1.574	(1.186) 0.860	(1.409) 0.119	(1.563) 0.154
as.factor(market)58	0.676	−0.743	−0.053	1.518

Table 15: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)59	(1.151)	(1.030)	(1.102)	(1.137)
as.factor(market)60	-0.172 (1.238)	0.795 (1.083)	1.618 (1.174)	1.775 (1.125)
as.factor(market)61	2.105 (1.144)	-0.383 (0.978)	0.493 (1.013)	2.899** (1.089)
as.factor(market)62	-0.498 (0.990)	-0.212 (0.993)	0.549 (0.991)	2.487* (1.101)
as.factor(market)63	-0.308 (1.110)	-0.522 (1.265)	2.449* (1.226)	1.769 (1.387)
as.factor(market)64	-1.154 (1.073)	1.260 (1.055)	-0.748 (1.151)	3.130* (1.306)
as.factor(market)65	-1.780 (1.103)	1.124 (1.038)	1.923 (1.260)	1.013 (1.167)
as.factor(market)66	-4.755*** (1.420)	1.301 (1.454)	-1.747 (1.830)	0.179 (1.588)
as.factor(market)68	-0.642 (1.076)	0.859 (0.986)	2.511* (1.137)	1.208 (1.211)
as.factor(market)69	-0.005 (1.085)	-1.123 (1.261)	-0.391 (1.820)	5.826** (1.917)
as.factor(market)70	-2.330* (1.141)	0.846 (1.242)	0.511 (1.225)	3.762* (1.598)
as.factor(market)71	-0.807 (1.136)	0.611 (1.035)	-0.042 (1.172)	1.416 (1.537)
as.factor(market)72	-1.223 (1.087)	0.186 (1.157)	-0.254 (1.280)	0.477 (1.376)
	0.927	0.474	-1.083	1.241

Table 15: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)73	(1.229) -0.385 (1.065)	(1.093) -0.756 (1.137)	(1.302) 1.677 (1.239)	(1.479) 3.467** (1.312)
as.factor(market)74	-0.245 (1.102)	-1.279 (1.078)	1.130 (1.165)	0.465 (1.237)
as.factor(market)75	-1.740 (1.102)	-1.209 (1.006)	2.171* (1.079)	1.648 (1.219)
as.factor(market)77	0.200 (1.173)	-1.153 (1.311)	1.628 (1.263)	2.886* (1.384)
as.factor(market)78	-1.076 (1.412)	-1.501 (1.116)	0.317 (1.254)	0.187 (1.260)
as.factor(market)79	0.607 (1.250)	-0.664 (1.132)	2.300 (1.264)	2.076 (1.405)
as.factor(market)80	-1.188 (1.075)	-1.647 (1.086)	0.631 (1.184)	1.583 (1.328)
as.factor(market)81	0.027 (1.029)	-0.020 (0.983)	0.347 (1.200)	1.487 (1.252)
as.factor(market)82	-0.898 (1.116)	-2.030 (1.133)	2.167 (1.271)	2.046 (1.253)
as.factor(market)84	-1.382 (1.188)	-1.292 (1.097)	-0.301 (1.020)	1.505 (1.116)
as.factor(market)85	0.087 (1.089)	-1.039 (0.982)	-1.214 (1.200)	2.047 (1.155)
as.factor(market)86	-0.684 (0.969)	-0.757 (1.089)	1.455 (1.170)	2.750* (1.234)
as.factor(market)87	-1.315	0.155	0.624	2.076

Table 15: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)88	(1.405) 0.205 (1.133)	(1.141) −0.245 (1.156)	(1.090) 1.370 (1.094)	(1.247) 2.611* (1.156)
as.factor(market)90	−0.288 (1.061)	0.593 (1.103)	0.987 (1.386)	4.304*** (1.168)
as.factor(market)91	−0.908 (1.463)	−3.115* (1.216)	−1.159 (1.275)	0.509 (1.221)
as.factor(market)92	−2.269 (2.598)	−0.291 (1.332)	1.923 (1.533)	2.414 (1.340)
as.factor(market)93	0.533 (0.989)	1.847 (1.133)	1.405 (1.351)	2.934* (1.297)
as.factor(market)94	−1.807 (2.020)	−2.360 (1.387)	1.357 (1.547)	2.287 (1.348)
as.factor(market)95	−0.894 (1.062)	−0.886 (0.983)	1.626 (1.081)	−0.231 (1.191)
as.factor(market)96	−1.265 (1.042)	0.912 (1.008)	1.563 (1.241)	0.426 (1.259)
as.factor(market)97	−3.575 (3.305)	3.089 (3.808)	0.659 (1.455)	3.510* (1.478)
as.factor(market)98		0.151 (6.869)		
as.factor(market)99				9.826 (5.504)
uik_population	−0.002*** (0.0001)	−0.002*** (0.0001)	−0.001*** (0.0001)	−0.002*** (0.0001)

Table 15: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
Observations	(1) 7,998	(2) 7,127	(3) 7,011	(4) 8,008
R <sup>2</sup>	0.041	0.048	0.031	0.050
Adjusted R <sup>2</sup>	-0.020	-0.015	-0.030	-0.005

Note:

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

## **G Robustness checks: salary test for vote share**

Figure 14: Regression results: effect of geographical proximity on vote share at 2012 presidential elections (market and region FE included)

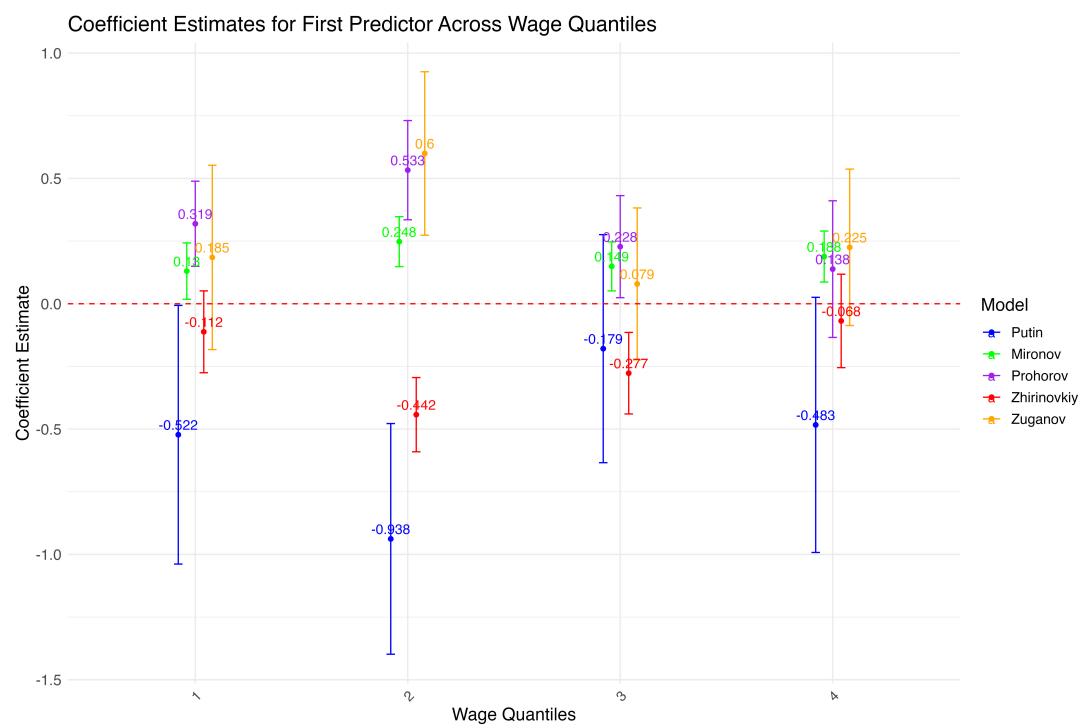


Figure 15: Regression results: effect of geographical proximity on vote share at 2016 parliamentary elections (market and region FE included)

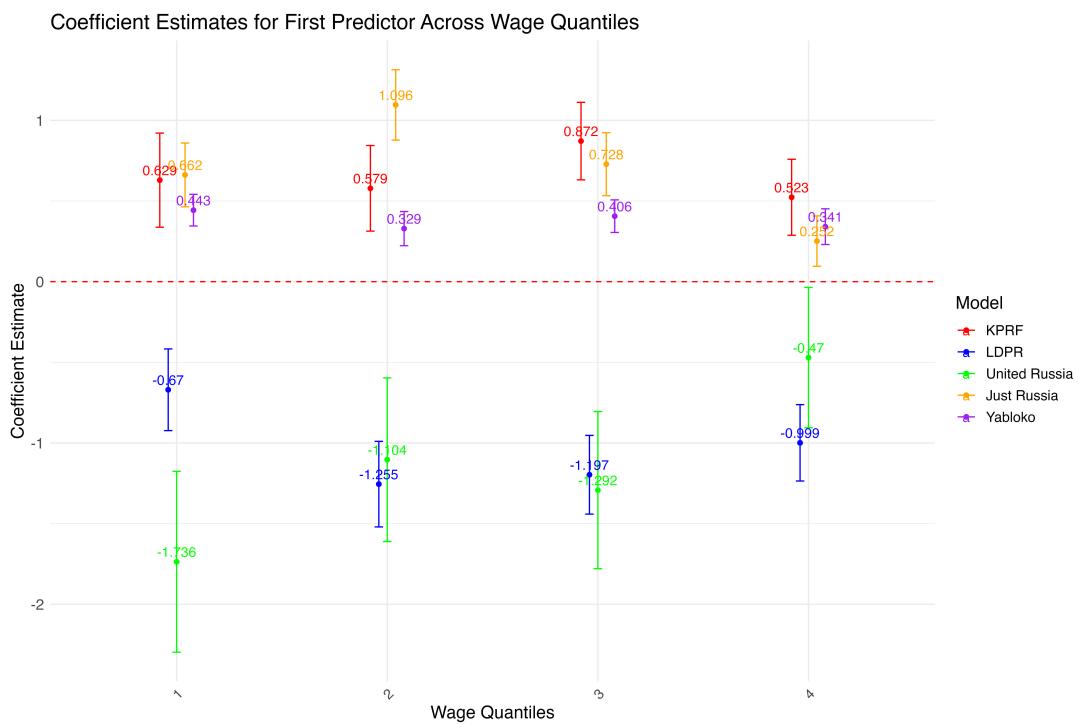
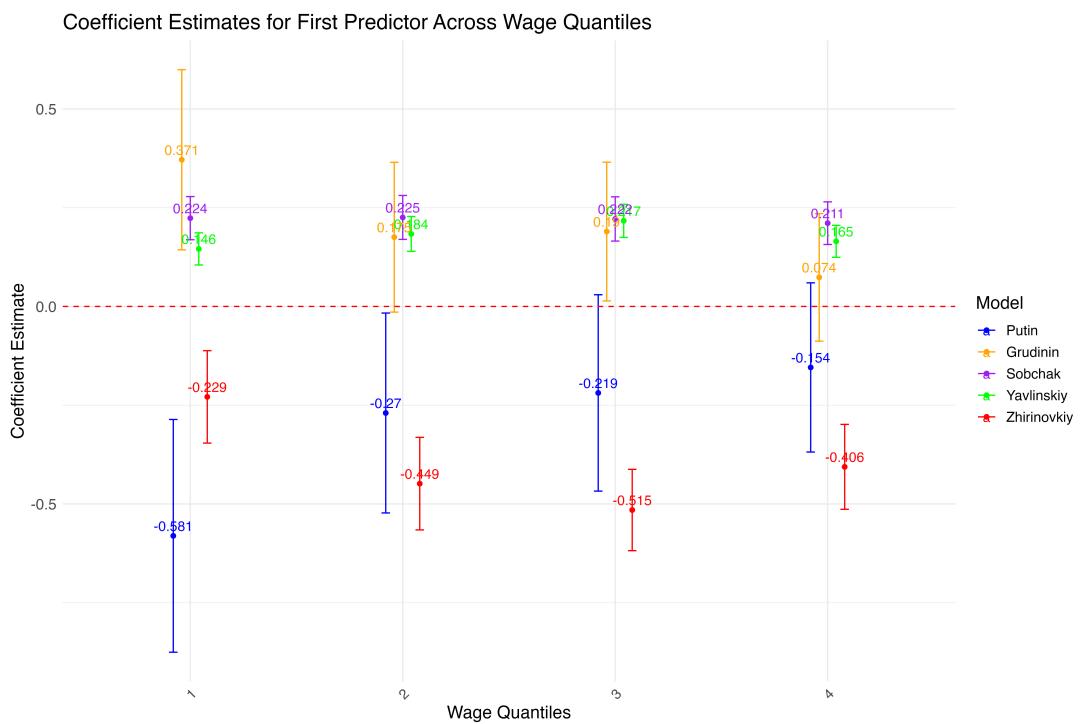


Figure 16: Regression results: effect of geographical proximity on vote share at 2018 presidential elections (market and region FE included)



## H Robustness checks: salary test for vote share (Regression tables for UR and Putin)

Table 16: Regression results by wage quartiles: effect of geographical proximity on Putin's vote share at 2012 presidential elections (market and region FE included)

	<i>Dependent variable:</i>			
	Wage 1st quar			
	(1)	(2)	(3)	(4)
proximity	-0.480 (0.299)	-0.917*** (0.257)	-0.348 (0.259)	-0.470 (0.287)
as.factor(market)02	-0.127 (1.048)	0.654 (0.985)	-0.793 (1.033)	-1.979 (1.251)
as.factor(market)03	0.612 (1.082)	-0.242 (0.854)	0.950 (1.068)	-1.130 (1.310)
as.factor(market)05	2.576 (1.861)	1.553 (1.387)	0.570 (1.820)	-0.544 (1.459)
as.factor(market)06	0.482 (3.767)	2.056 (1.376)	0.241 (1.834)	-2.299 (1.660)
as.factor(market)07	-0.250 (2.832)	-2.226 (1.400)	1.956 (1.786)	-2.719 (1.727)
as.factor(market)08	0.937 (1.012)	-1.185 (0.941)	-0.609 (1.052)	1.876 (1.360)
as.factor(market)09	2.353 (1.271)	-0.262 (1.057)	-1.494 (1.525)	-1.749 (1.372)
as.factor(market)10	0.498 (0.930)	1.189 (0.975)	0.468 (0.952)	-0.680 (1.469)
as.factor(market)11	0.663 (0.985)	0.990 (0.910)	0.541 (0.986)	-1.173 (1.340)

Table 16: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)12	0.138 (2.090)	2.579* (1.176)	0.162 (1.792)	-3.276* (1.511)
as.factor(market)13	0.356 (1.038)	-0.227 (0.902)	1.834 (1.104)	-1.157 (1.294)
as.factor(market)14	0.658 (1.014)	-0.278 (0.920)	-0.009 (0.965)	-0.321 (1.332)
as.factor(market)15	2.073 (1.241)	0.155 (0.948)	-1.179 (1.099)	-1.918 (1.321)
as.factor(market)16	0.179 (1.114)	0.294 (0.913)	-0.039 (1.069)	-1.742 (1.331)
as.factor(market)17	0.694 (1.121)	1.838 (0.970)	0.297 (0.983)	-2.318 (1.239)
as.factor(market)18	-0.051 (1.032)	0.904 (0.895)	-0.688 (0.972)	-2.081 (1.241)
as.factor(market)19	-0.998 (1.624)	0.369 (1.074)	-0.521 (1.276)	-1.735 (1.563)
as.factor(market)20	1.026 (1.051)	-0.029 (0.963)	0.954 (1.044)	-0.401 (1.275)
as.factor(market)21	1.351 (1.078)	0.525 (1.174)	-1.420 (1.429)	-2.155 (1.462)
as.factor(market)22	-0.772 (0.982)	0.663 (0.973)	-1.545 (1.110)	-0.681 (1.307)
as.factor(market)23	-0.337 (0.986)	-0.860 (1.012)	1.863 (1.098)	-2.001 (1.366)
as.factor(market)24	0.430 (1.195)	0.500 (1.066)	-1.903 (1.096)	-0.337 (1.302)

Table 16: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar (1)	Wage 2nd quar (2)	Wage 3rd quar (3)	Wage 4th quar (4)
as.factor(market)25	-1.394 (1.124)	-0.191 (1.102)	-1.323 (1.224)	-1.976 (1.512)
as.factor(market)26	2.912** (1.037)	0.384 (1.017)	-0.031 (1.117)	-0.345 (1.292)
as.factor(market)27	-0.116 (1.077)	1.438 (0.995)	-0.879 (1.224)	-3.935** (1.332)
as.factor(market)28	0.178 (1.066)	1.140 (0.980)	-0.272 (1.036)	-2.487 (1.316)
as.factor(market)29	-0.931 (1.287)	1.934 (1.063)	-1.749 (1.181)	0.593 (1.308)
as.factor(market)30	0.453 (1.154)	1.780 (1.093)	-1.240 (1.059)	-1.653 (1.335)
as.factor(market)31	0.744 (1.113)	0.570 (1.155)	-1.380 (1.071)	-1.852 (1.317)
as.factor(market)32	1.061 (0.979)	-0.519 (0.952)	-1.793 (1.089)	-3.715** (1.278)
as.factor(market)33	-0.553 (1.025)	0.320 (0.930)	0.479 (1.132)	-3.338** (1.253)
as.factor(market)35	0.336 (1.022)	-0.428 (0.867)	-0.775 (1.013)	-1.062 (1.389)
as.factor(market)36	1.241 (1.239)	0.855 (0.921)	0.512 (1.175)	-0.512 (1.217)
as.factor(market)37	0.302 (1.181)	-0.462 (1.031)	-2.062 (1.070)	-2.371* (1.189)
as.factor(market)38	-1.909 (1.031)	0.245 (0.960)	0.205 (1.053)	-1.049 (1.362)

Table 16: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)39	8.913 (5.154)	-2.558 (1.608)	-3.688* (1.439)	-2.081 (1.928)
as.factor(market)41	1.337 (1.008)	0.193 (1.172)	-0.755 (2.092)	-3.364 (1.991)
as.factor(market)42	-0.220 (1.020)	0.182 (1.000)	-0.786 (1.252)	-0.354 (1.376)
as.factor(market)43	1.024 (0.948)	0.348 (1.053)	-1.333 (1.777)	-1.694 (2.059)
as.factor(market)45	-0.100 (1.085)	-0.121 (1.058)	-1.919 (1.259)	-2.222 (1.776)
as.factor(market)46	0.867 (0.908)	-0.524 (1.486)	-3.505 (2.196)	-3.762 (2.459)
as.factor(market)47	0.196 (1.078)	5.707*** (1.526)	-1.132 (1.901)	-4.051 (2.920)
as.factor(market)49	0.242 (1.057)	1.065 (1.201)	0.010 (1.479)	-1.556 (1.883)
as.factor(market)50	3.869 (2.425)	-0.928 (1.136)	-1.422 (1.300)	-1.613 (1.304)
as.factor(market)51	4.895 (2.545)	-1.306 (1.073)	-0.011 (1.439)	-0.566 (1.277)
as.factor(market)52	-0.434 (0.973)	-0.894 (1.048)	0.381 (1.218)	0.340 (1.966)
as.factor(market)53	-1.584 (1.073)	-1.552 (1.001)	-0.669 (0.992)	-1.477 (1.269)
as.factor(market)55	0.089 (0.996)	-0.976 (0.979)	0.261 (1.078)	-1.908 (1.282)

Table 16: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)56	0.596 (0.976)	-0.370 (1.106)	-0.035 (1.393)	-0.404 (1.661)
as.factor(market)58	-0.387 (1.143)	-0.088 (0.965)	0.525 (0.996)	-2.364 (1.253)
as.factor(market)59	0.195 (1.174)	0.878 (1.152)	-0.114 (1.068)	-1.664 (1.243)
as.factor(market)60	0.831 (1.094)	0.081 (0.870)	-1.008 (0.967)	-0.344 (1.258)
as.factor(market)61	2.618** (0.970)	1.262 (0.888)	-0.745 (0.963)	0.835 (1.245)
as.factor(market)62	-1.040 (1.067)	-0.693 (1.179)	-1.655 (1.215)	-1.503 (1.454)
as.factor(market)63	-0.698 (1.025)	0.354 (1.015)	-1.327 (1.037)	0.062 (1.568)
as.factor(market)64	0.294 (1.072)	1.962 (1.044)	-1.884 (1.084)	-2.046 (1.308)
as.factor(market)65	1.398 (1.355)	0.703 (1.491)	-0.461 (1.636)	-1.577 (2.268)
as.factor(market)66	0.061 (1.055)	-0.363 (1.007)	-1.729 (1.032)	-0.249 (1.333)
as.factor(market)68	1.222 (1.047)	-0.469 (1.220)	-2.001 (1.780)	-0.322 (2.069)
as.factor(market)69	-1.584 (1.163)	1.353 (1.102)	0.927 (1.336)	-1.068 (1.804)
as.factor(market)70	0.842 (1.034)	-0.890 (0.953)	-2.017 (1.104)	-1.364 (1.716)

Table 16: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)71	1.996 (1.068)	-0.084 (1.024)	0.990 (1.153)	-2.331 (1.734)
as.factor(market)72	1.697 (1.210)	-0.928 (1.180)	-1.353 (1.132)	-2.280 (1.504)
as.factor(market)73	1.216 (1.030)	2.231* (1.065)	0.126 (1.138)	-0.451 (1.414)
as.factor(market)74	0.748 (1.075)	-0.087 (1.025)	0.036 (1.130)	-0.559 (1.372)
as.factor(market)75	-0.098 (1.078)	0.721 (0.984)	-1.128 (1.090)	0.299 (1.328)
as.factor(market)77	0.272 (1.265)	0.837 (1.121)	-3.887** (1.209)	-0.409 (1.539)
as.factor(market)78	0.743 (1.282)	0.273 (1.091)	1.176 (1.194)	-1.119 (1.381)
as.factor(market)79	1.155 (1.195)	-0.778 (1.044)	0.357 (1.253)	-2.705 (1.632)
as.factor(market)80	1.290 (1.020)	1.518 (1.062)	-2.395* (1.108)	0.080 (1.469)
as.factor(market)81	0.684 (0.978)	0.415 (0.910)	0.260 (1.100)	-0.497 (1.373)
as.factor(market)82	0.097 (1.098)	-0.492 (1.068)	-0.223 (1.117)	0.163 (1.499)
as.factor(market)84	-0.617 (1.161)	0.110 (0.993)	-0.082 (1.019)	-0.452 (1.243)
as.factor(market)85	-1.640 (1.031)	0.872 (0.941)	-0.289 (1.053)	-1.187 (1.263)

Table 16: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)86	1.339 (0.946)	-0.106 (0.925)	-1.681 (1.120)	-1.701 (1.401)
as.factor(market)87	-0.028 (1.319)	0.143 (0.959)	0.019 (1.136)	0.012 (1.400)
as.factor(market)88	-0.247 (1.118)	0.212 (1.050)	-1.362 (1.082)	-0.594 (1.274)
as.factor(market)90	-0.876 (1.016)	2.460* (1.095)	0.241 (1.281)	-0.367 (1.298)
as.factor(market)91	-0.369 (1.428)	0.291 (1.035)	-3.333* (1.585)	-1.882 (1.351)
as.factor(market)92	5.280 (3.231)	-0.629 (1.163)	-1.193 (1.300)	-3.167* (1.569)
as.factor(market)93	0.538 (0.965)	0.537 (1.161)	0.877 (1.066)	-1.241 (1.472)
as.factor(market)94	-1.840 (1.881)	0.358 (1.223)	0.357 (2.157)	-0.955 (1.397)
as.factor(market)95	-0.603 (1.018)	-0.375 (0.974)	-0.057 (0.991)	-0.992 (1.279)
as.factor(market)96	0.373 (1.000)	0.650 (0.944)	-2.283* (1.155)	-3.319* (1.400)
as.factor(market)97	-3.474 (3.053)	0.667 (1.484)	1.970 (2.291)	-3.725* (1.527)
as.factor(market)98		5.431 (6.352)		
as.factor(market)99				-2.061 (4.997)

Table 16: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
uik_population	-0.0002 (0.0001)	-0.0005*** (0.0001)	-0.0002 (0.0001)	-0.001*** (0.0001)
Observations	6,652	5,786	5,598	5,394
R <sup>2</sup>	0.018	0.028	0.027	0.029
Adjusted R <sup>2</sup>	-0.042	-0.033	-0.040	-0.030
<i>Note:</i>	*p<0.05; **p<0.01; ***p<0.001			

Table 17: Regression results by wage quartiles: effect of geographical proximity on UR's vote share at 2016 parliamentary elections (market and region FE included)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
proximity	-1.736*** (0.286)	-1.104*** (0.259)	-1.292*** (0.248)	-0.470* (0.222)
as.factor(market)02	3.060** (1.099)	1.262 (1.092)	-0.813 (0.981)	-0.901 (1.001)
as.factor(market)03	0.629 (1.068)	1.314 (1.065)	-1.269 (0.985)	-0.302 (1.060)
as.factor(market)05	3.007 (1.990)	0.276 (2.579)	-0.943 (1.316)	0.197 (1.299)

Table 17: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)06	3.993 (3.293)	0.664 (1.601)	0.462 (1.647)	1.523 (1.403)
as.factor(market)07	-0.604 (2.486)	2.008 (1.531)	0.375 (1.471)	-0.043 (1.221)
as.factor(market)08	1.101 (0.997)	0.303 (1.008)	0.606 (1.126)	0.093 (1.041)
as.factor(market)09	2.885 (1.585)	0.042 (1.104)	-2.448 (1.377)	-1.151 (1.094)
as.factor(market)10	0.771 (0.919)	1.003 (1.028)	0.144 (1.125)	-1.821 (1.070)
as.factor(market)11	0.742 (0.989)	2.185* (0.958)	-0.647 (1.056)	1.304 (1.062)
as.factor(market)12	-0.701 (2.166)	8.909*** (1.436)	-1.651 (1.366)	1.586 (1.187)
as.factor(market)13	1.731 (1.037)	0.905 (0.979)	0.149 (1.112)	-0.560 (1.031)
as.factor(market)14	0.292 (1.039)	0.307 (0.995)	-0.046 (1.041)	-0.418 (1.019)
as.factor(market)15	-0.492 (1.172)	2.233* (1.042)	0.365 (1.108)	1.722 (1.043)
as.factor(market)16	0.259 (1.088)	0.794 (1.026)	-1.620 (1.080)	0.393 (1.038)
as.factor(market)17	2.289 (1.200)	1.371 (1.015)	-0.779 (1.006)	-0.225 (0.977)
as.factor(market)18	1.241 (1.036)	0.422 (0.996)	-0.591 (1.019)	0.739 (0.951)

Table 17: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)19	-1.724 (1.730)	1.231 (1.492)	0.430 (1.229)	-0.211 (1.149)
as.factor(market)20	0.128 (1.060)	2.543* (1.060)	0.076 (1.042)	1.276 (1.022)
as.factor(market)21	-0.568 (1.136)	0.784 (1.179)	-1.365 (1.281)	-1.026 (1.174)
as.factor(market)22	-0.195 (1.002)	2.175* (1.089)	-0.387 (1.131)	-0.021 (1.054)
as.factor(market)23	1.372 (1.043)	0.961 (1.025)	-0.434 (1.116)	0.655 (1.142)
as.factor(market)24	-0.324 (1.162)	2.172 (1.149)	-0.609 (1.037)	0.970 (1.036)
as.factor(market)25	1.345 (1.136)	-0.486 (1.215)	-0.710 (1.285)	0.511 (1.175)
as.factor(market)26	-0.301 (1.039)	0.047 (1.049)	-1.083 (1.145)	-0.823 (1.049)
as.factor(market)27	0.224 (1.110)	-0.537 (1.081)	-0.605 (1.160)	-0.251 (1.051)
as.factor(market)28	0.149 (1.068)	2.620* (1.037)	0.140 (1.099)	0.420 (1.079)
as.factor(market)29	0.205 (1.206)	0.588 (1.142)	1.111 (1.155)	-0.003 (1.067)
as.factor(market)30	-1.857 (1.145)	0.895 (1.174)	-0.843 (1.079)	2.268* (1.087)
as.factor(market)31	0.817 (1.162)	0.512 (1.239)	1.841 (1.067)	0.659 (1.020)

Table 17: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)32	0.568 (0.975)	0.114 (0.996)	-1.742 (1.172)	-0.873 (1.003)
as.factor(market)33	-0.729 (1.048)	0.898 (1.004)	-0.878 (1.211)	-0.114 (0.981)
as.factor(market)35	-0.630 (1.023)	0.466 (0.956)	-1.697 (1.013)	-0.181 (1.039)
as.factor(market)36	-1.016 (1.148)	0.129 (1.097)	-0.105 (1.060)	0.430 (0.969)
as.factor(market)37	0.188 (1.201)	0.568 (1.026)	-2.452* (1.183)	-0.308 (0.935)
as.factor(market)38	-2.098* (1.040)	0.628 (1.059)	-0.491 (1.099)	1.085 (1.058)
as.factor(market)39		0.311 (1.647)	0.689 (1.542)	1.753 (1.483)
as.factor(market)41	1.270 (1.048)	1.046 (1.315)	0.114 (1.606)	-0.297 (2.102)
as.factor(market)42	1.154 (1.027)	0.980 (1.154)	-0.432 (1.209)	0.684 (1.058)
as.factor(market)43	-0.373 (0.985)	-0.445 (1.117)	1.478 (1.613)	1.332 (1.662)
as.factor(market)45	-0.167 (1.150)	1.039 (1.152)	0.413 (1.135)	-0.012 (1.373)
as.factor(market)46	0.231 (0.958)	2.845 (1.720)	-0.334 (2.006)	1.767 (1.654)
as.factor(market)47	-2.002 (1.145)	-0.817 (1.491)	0.511 (1.796)	4.337 (2.324)

Table 17: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)49	-0.283 (1.068)	2.910* (1.237)	-1.717 (1.447)	-0.046 (1.448)
as.factor(market)50	-2.036 (2.140)	0.274 (1.256)	-2.554 (1.343)	0.982 (1.044)
as.factor(market)51	1.644 (1.596)	0.935 (1.307)	-1.041 (1.198)	0.176 (1.015)
as.factor(market)52	1.549 (1.032)	-1.047 (1.135)	0.402 (1.252)	-0.966 (1.335)
as.factor(market)53	-1.184 (1.031)	0.691 (1.004)	-0.245 (1.034)	0.889 (1.021)
as.factor(market)55	0.787 (1.029)	0.621 (1.040)	0.018 (1.225)	-1.099 (0.971)
as.factor(market)56	1.370 (1.042)	0.749 (1.169)	1.430 (1.363)	-0.202 (1.349)
as.factor(market)58	0.188 (1.143)	1.326 (1.028)	-1.938 (1.082)	-0.691 (0.995)
as.factor(market)59	0.017 (1.233)	0.667 (1.089)	-0.976 (1.138)	0.179 (0.982)
as.factor(market)60	-0.253 (1.156)	0.803 (0.971)	-0.594 (0.991)	0.441 (0.950)
as.factor(market)61	-0.586 (0.989)	0.734 (0.991)	-0.032 (0.972)	-0.522 (0.958)
as.factor(market)62	0.688 (1.104)	0.905 (1.285)	0.792 (1.202)	1.059 (1.197)
as.factor(market)63	0.048 (1.064)	1.241 (1.066)	-1.049 (1.121)	0.194 (1.148)

Table 17: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)64	1.074 (1.104)	0.521 (1.029)	0.633 (1.264)	-2.169* (1.026)
as.factor(market)65	-1.874 (1.384)	2.474 (1.450)	-0.678 (1.803)	1.530 (1.403)
as.factor(market)66	0.436 (1.040)	0.686 (1.000)	0.055 (1.111)	0.803 (1.065)
as.factor(market)68	1.271 (1.075)	1.517 (1.361)	-1.468 (1.591)	1.957 (1.655)
as.factor(market)69	0.413 (1.135)	0.560 (1.272)	0.693 (1.184)	-0.276 (1.393)
as.factor(market)70	-1.824 (1.035)	1.666 (1.065)	-0.311 (1.149)	0.235 (1.326)
as.factor(market)71	-0.474 (1.086)	1.149 (1.171)	0.110 (1.230)	-0.009 (1.191)
as.factor(market)72	0.471 (1.180)	-1.035 (1.089)	0.567 (1.266)	0.996 (1.276)
as.factor(market)73	0.281 (1.062)	-0.820 (1.134)	-0.590 (1.220)	-0.399 (1.154)
as.factor(market)74	0.172 (1.116)	-0.130 (1.066)	-0.654 (1.142)	-0.112 (1.087)
as.factor(market)75	0.908 (1.045)	0.420 (1.035)	-1.432 (1.067)	0.054 (1.071)
as.factor(market)77	0.400 (1.223)	-0.563 (1.287)	0.365 (1.221)	-0.462 (1.194)
as.factor(market)78	0.055 (1.361)	0.936 (1.126)	-0.994 (1.234)	-0.187 (1.108)

Table 17: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)79	-0.669 (1.219)	0.156 (1.145)	-0.328 (1.245)	0.025 (1.212)
as.factor(market)80	0.806 (1.055)	-0.542 (1.135)	-0.744 (1.129)	1.067 (1.157)
as.factor(market)81	-0.302 (1.029)	0.384 (0.990)	-0.314 (1.142)	1.427 (1.085)
as.factor(market)82	-0.210 (1.132)	1.792 (1.103)	0.360 (1.244)	-0.067 (1.112)
as.factor(market)84	-0.209 (1.135)	0.774 (1.135)	-1.240 (1.030)	-1.562 (0.981)
as.factor(market)85	-0.459 (1.067)	0.913 (0.996)	-0.871 (1.145)	-0.030 (1.000)
as.factor(market)86	0.383 (0.966)	0.701 (1.094)	-0.309 (1.138)	1.549 (1.075)
as.factor(market)87	-0.827 (1.357)	0.903 (1.156)	-0.688 (1.072)	0.574 (1.097)
as.factor(market)88	-0.837 (1.111)	0.915 (1.186)	-0.335 (1.081)	-1.280 (1.011)
as.factor(market)90	0.468 (1.063)	0.158 (1.121)	-2.222 (1.311)	1.972 (1.025)
as.factor(market)91	2.285 (1.546)	0.832 (1.180)	-0.233 (1.255)	-1.768 (1.066)
as.factor(market)92	-1.652 (2.564)	-0.296 (1.376)	1.869 (1.509)	-0.499 (1.177)
as.factor(market)93	-0.982 (1.001)	1.840 (1.138)	0.506 (1.259)	-0.479 (1.125)

Table 17: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)94	2.039 (2.249)	1.197 (1.353)	-0.137 (1.491)	1.728 (1.166)
as.factor(market)95	-0.101 (1.038)	-0.108 (1.011)	-0.045 (1.024)	0.438 (1.033)
as.factor(market)96	-1.219 (1.048)	0.150 (1.018)	-1.722 (1.176)	-0.279 (1.095)
as.factor(market)97	1.171 (3.547)	-2.852 (3.377)	-3.697** (1.431)	0.208 (1.288)
as.factor(market)98		2.562 (6.877)		
as.factor(market)99				0.098 (4.749)
uik_population	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)	-0.001*** (0.0001)
Observations	8,000	6,823	7,169	7,610
R <sup>2</sup>	0.024	0.040	0.023	0.037
Adjusted R <sup>2</sup>	-0.036	-0.024	-0.039	-0.021

*Note:*

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

Table 18: Regression results by wage quartiles: effect of geographical proximity on UR's vote share at 2018 parliamentary elections (market and region FE included)

	<i>Dependent variable:</i>			
	Wage 1st quar (1)	Wage 2nd quar (2)	Wage 3rd quar (3)	Wage 4th quar (4)
proximity	−0.581*** (0.150)	−0.270* (0.129)	−0.219 (0.127)	−0.154 (0.109)
as.factor(market)02	1.367* (0.560)	−0.473 (0.561)	−0.206 (0.505)	0.051 (0.498)
as.factor(market)03	−0.045 (0.584)	−1.062* (0.515)	−0.700 (0.506)	0.751 (0.529)
as.factor(market)05	1.199 (1.057)	−3.020* (1.275)	0.056 (0.675)	0.545 (0.659)
as.factor(market)06	1.725 (1.752)	−2.060** (0.778)	0.447 (0.860)	0.406 (0.698)
as.factor(market)07	0.033 (1.024)	−0.319 (0.856)	−0.315 (0.755)	−0.178 (0.590)
as.factor(market)08	0.806 (0.530)	−1.097* (0.492)	0.559 (0.596)	0.992 (0.521)
as.factor(market)09	1.921* (0.867)	−0.957 (0.543)	−0.148 (0.700)	−1.012 (0.541)
as.factor(market)10	0.597 (0.491)	0.058 (0.491)	−0.252 (0.561)	0.139 (0.544)
as.factor(market)11	1.161* (0.532)	0.137 (0.473)	−0.407 (0.541)	0.690 (0.535)
as.factor(market)12	0.020 (1.153)	3.199*** (0.711)	0.421 (0.701)	−0.022 (0.588)
as.factor(market)13	0.405	−0.060	0.517	0.276

Table 18: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)14	(0.558) 0.802 (0.553)	(0.480) −0.591 (0.491)	(0.582) 0.366 (0.541)	(0.516) 0.566 (0.506)
as.factor(market)15	0.777 (0.606)	−0.759 (0.528)	0.192 (0.561)	0.340 (0.508)
as.factor(market)16	0.450 (0.579)	−0.458 (0.506)	0.124 (0.557)	1.098* (0.520)
as.factor(market)17	2.194*** (0.613)	−0.715 (0.506)	0.212 (0.515)	0.601 (0.490)
as.factor(market)18	0.126 (0.545)	−0.398 (0.497)	−0.902 (0.524)	0.835 (0.479)
as.factor(market)19	0.366 (0.910)	−0.675 (0.729)	−0.221 (0.625)	0.230 (0.580)
as.factor(market)20	0.432 (0.555)	0.131 (0.527)	−0.004 (0.540)	0.495 (0.512)
as.factor(market)21	1.213* (0.592)	−0.828 (0.589)	0.976 (0.653)	−0.210 (0.590)
as.factor(market)22	0.202 (0.534)	−0.066 (0.533)	0.657 (0.585)	−0.465 (0.532)
as.factor(market)23	0.813 (0.552)	−0.291 (0.525)	−0.101 (0.574)	0.822 (0.577)
as.factor(market)24	1.165 (0.614)	−0.230 (0.559)	0.463 (0.534)	0.996 (0.513)
as.factor(market)25	0.631 (0.608)	−1.038 (0.569)	−0.779 (0.679)	0.041 (0.597)
as.factor(market)26	1.077	0.057	−0.703	0.121

Table 18: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)27	(0.564) 0.721 (0.606)	(0.514) −0.767 (0.523)	(0.592) 0.786 (0.588)	(0.518) 0.327 (0.527)
as.factor(market)28	0.704 (0.569)	−0.175 (0.509)	0.192 (0.566)	0.633 (0.546)
as.factor(market)29	−0.399 (0.654)	−0.245 (0.558)	−0.693 (0.583)	0.287 (0.524)
as.factor(market)30	0.084 (0.603)	0.001 (0.593)	−0.367 (0.542)	0.199 (0.533)
as.factor(market)31	0.920 (0.610)	−0.398 (0.610)	0.037 (0.553)	0.794 (0.514)
as.factor(market)32	1.237* (0.534)	−0.664 (0.483)	−0.418 (0.604)	0.508 (0.509)
as.factor(market)33	0.204 (0.560)	−0.507 (0.494)	0.535 (0.629)	0.091 (0.495)
as.factor(market)35	−0.023 (0.542)	−0.536 (0.477)	−0.422 (0.526)	0.783 (0.522)
as.factor(market)36	0.696 (0.610)	−0.860 (0.538)	0.047 (0.545)	0.002 (0.487)
as.factor(market)37	0.432 (0.634)	−0.522 (0.511)	−1.575** (0.598)	0.654 (0.469)
as.factor(market)38	0.372 (0.550)	0.485 (0.521)	−0.914 (0.572)	0.164 (0.537)
as.factor(market)39		−0.793 (0.816)	0.620 (0.804)	0.783 (0.753)
as.factor(market)41	1.747**	0.584	0.345	0.182

Table 18: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)42	(0.556) 0.901 (0.550)	(0.608) −1.216* (0.557)	(0.918) 0.014 (0.631)	(1.067) −0.358 (0.528)
as.factor(market)43	0.470 (0.528)	−1.042 (0.539)	−0.164 (0.871)	0.798 (0.816)
as.factor(market)45	−0.016 (0.611)	−0.121 (0.554)	−1.178* (0.597)	1.093 (0.697)
as.factor(market)46	0.940 (0.508)	0.418 (0.727)	−0.300 (1.303)	0.482 (0.840)
as.factor(market)47	−0.887 (0.611)	−1.343 (0.709)	0.718 (0.966)	−1.079 (1.180)
as.factor(market)49	−0.499 (0.565)	−0.225 (0.601)	−0.110 (0.778)	−0.217 (0.744)
as.factor(market)50	0.001 (1.177)	−1.527* (0.619)	−1.160 (0.678)	0.338 (0.523)
as.factor(market)51	−0.087 (0.991)	−1.103 (0.655)	−0.488 (0.615)	0.580 (0.506)
as.factor(market)52	0.617 (0.547)	−0.526 (0.562)	−0.599 (0.641)	−0.119 (0.678)
as.factor(market)53	0.293 (0.550)	−0.246 (0.493)	−0.129 (0.532)	0.517 (0.514)
as.factor(market)55	0.858 (0.555)	−0.974 (0.503)	0.050 (0.657)	−0.420 (0.484)
as.factor(market)56	0.586 (0.546)	0.336 (0.586)	0.628 (0.712)	0.869 (0.685)
as.factor(market)58	0.002	0.114	0.039	0.043

Table 18: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar (1)	Wage 2nd quar (2)	Wage 3rd quar (3)	Wage 4th quar (4)
as.factor(market)59	(0.609) 0.747 (0.655)	(0.509) −0.753 (0.535)	(0.557) −0.338 (0.593)	(0.498) −0.341 (0.493)
as.factor(market)60	0.709 (0.605)	−0.313 (0.483)	0.401 (0.511)	0.614 (0.477)
as.factor(market)61	0.316 (0.524)	−0.405 (0.491)	−0.105 (0.500)	0.268 (0.482)
as.factor(market)62	1.434* (0.588)	0.466 (0.625)	0.064 (0.619)	−0.165 (0.608)
as.factor(market)63	0.166 (0.568)	−0.911 (0.522)	0.515 (0.581)	0.480 (0.572)
as.factor(market)64	0.112 (0.584)	−0.121 (0.513)	1.713** (0.637)	−0.154 (0.511)
as.factor(market)65	−0.158 (0.752)	−0.202 (0.719)	0.889 (0.924)	−0.428 (0.696)
as.factor(market)66	−0.345 (0.569)	−0.125 (0.487)	0.079 (0.574)	0.440 (0.532)
as.factor(market)68	1.432* (0.574)	−1.165 (0.623)	−0.626 (0.919)	2.577** (0.840)
as.factor(market)69	0.810 (0.604)	−0.596 (0.614)	−0.110 (0.619)	0.519 (0.700)
as.factor(market)70	0.101 (0.601)	−0.386 (0.512)	−0.241 (0.592)	0.801 (0.673)
as.factor(market)71	−0.071 (0.575)	−0.256 (0.572)	−0.161 (0.646)	0.970 (0.603)
as.factor(market)72	0.744	−0.974	−0.534	0.187

Table 18: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar (1)	Wage 2nd quar (2)	Wage 3rd quar (3)	Wage 4th quar (4)
as.factor(market)73	(0.650) 0.092 (0.564)	(0.540) −0.374 (0.562)	(0.658) 0.832 (0.626)	(0.648) −1.157* (0.575)
as.factor(market)74	1.001 (0.583)	−0.713 (0.533)	0.990 (0.588)	1.115* (0.542)
as.factor(market)75	0.974 (0.583)	−0.918 (0.497)	−0.293 (0.545)	−0.672 (0.534)
as.factor(market)77	0.240 (0.621)	−0.371 (0.648)	−0.172 (0.638)	0.740 (0.606)
as.factor(market)78	0.543 (0.747)	−0.630 (0.552)	0.108 (0.633)	−0.254 (0.552)
as.factor(market)79	0.344 (0.662)	−1.279* (0.560)	0.947 (0.638)	0.480 (0.616)
as.factor(market)80	1.772** (0.569)	−0.649 (0.537)	0.639 (0.598)	0.546 (0.582)
as.factor(market)81	0.740 (0.545)	−0.294 (0.486)	−0.612 (0.606)	0.389 (0.548)
as.factor(market)82	0.647 (0.591)	−0.295 (0.560)	−0.191 (0.642)	−0.214 (0.549)
as.factor(market)84	−0.208 (0.629)	−0.855 (0.542)	−0.321 (0.515)	0.573 (0.489)
as.factor(market)85	0.201 (0.576)	−0.222 (0.485)	−1.290* (0.606)	0.332 (0.506)
as.factor(market)86	0.284 (0.513)	−0.738 (0.538)	0.006 (0.591)	0.726 (0.541)
as.factor(market)87	0.081	−0.601	0.679	0.945

Table 18: (continued)

	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
as.factor(market)88	(0.744) 0.815 (0.599)	(0.564) −0.117 (0.571)	(0.550) −0.266 (0.552)	(0.546) 0.123 (0.507)
as.factor(market)90	0.610 (0.561)	−0.565 (0.545)	−1.125 (0.700)	0.755 (0.512)
as.factor(market)91	1.440 (0.774)	−1.020 (0.601)	−0.457 (0.644)	−0.208 (0.535)
as.factor(market)92	1.451 (1.375)	−0.641 (0.658)	−0.851 (0.774)	−0.366 (0.587)
as.factor(market)93	0.309 (0.523)	0.273 (0.560)	0.037 (0.682)	−0.254 (0.568)
as.factor(market)94	1.790 (1.069)	−0.667 (0.685)	−0.672 (0.781)	0.071 (0.590)
as.factor(market)95	0.290 (0.562)	−1.026* (0.486)	0.198 (0.546)	0.810 (0.522)
as.factor(market)96	−0.588 (0.551)	−0.202 (0.498)	−0.200 (0.627)	0.225 (0.551)
as.factor(market)97	2.731 (1.749)	−0.615 (1.882)	−0.433 (0.735)	0.192 (0.648)
as.factor(market)98		−0.807 (3.395)		
as.factor(market)99				−0.501 (2.411)
uik_population	−0.0003*** (0.0001)	−0.0003*** (0.0001)	−0.0002*** (0.0001)	−0.0003*** (0.0001)

Table 18: (continued)

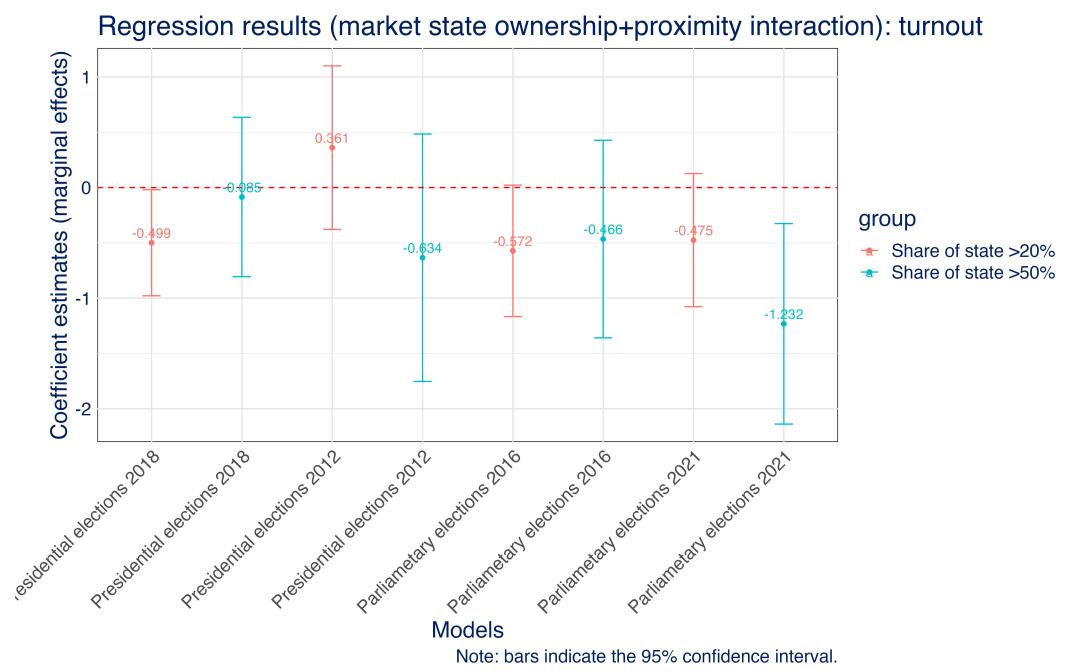
	<i>Dependent variable:</i>			
	Wage 1st quar	Wage 2nd quar	Wage 3rd quar	Wage 4th quar
	(1)	(2)	(3)	(4)
Observations	7,998	7,127	7,011	8,007
R <sup>2</sup>	0.020	0.025	0.022	0.023
Adjusted R <sup>2</sup>	-0.042	-0.039	-0.040	-0.033

Note:

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

## I Robustness checks: state share in market interaction

Figure 17: Regression results: effect of geographical proximity on turnout at federal parliamentary and presidential elections (region FE included)



## J Robustness checks: state share in market interaction. Regression table

Table 19: Regression results with market state wonership share interaction (market share  $\leq 20\%$ )

	Dependent variable:			
	Pres 2018 (1)	Pres 2012 (2)	Parl 2016 (3)	Parl 2021 (4)
proximity	2.044*** (0.154)	1.122*** (0.216)	3.086*** (0.191)	2.822*** (0.193)
market_dum	0.603 (0.380)	-0.756 (0.606)	0.705 (0.471)	0.431 (0.478)
as.factor(region)Yamalo-Neneckij avtonomnyj okrug	25.885*** (0.848)	35.929*** (3.440)	29.932*** (1.048)	26.523*** (1.086)
as.factor(region)Amurskaya oblast	-8.491*** (0.919)	3.785** (1.221)	-1.900 (1.134)	-0.537 (1.167)
as.factor(region)Arhangelskaya oblast	-6.630*** (0.839)	-3.363*** (1.010)	-5.852*** (1.041)	3.389** (1.064)
as.factor(region)Yaroslavskaya oblast				-0.909 (0.879)
as.factor(region)Astrahanskaya oblast	-7.100*** (1.012)	-3.947** (1.319)	-3.510** (1.248)	6.361*** (1.289)
as.factor(region)Belgorodskaya oblast	-1.258 (0.794)	9.716*** (0.962)	10.817*** (0.981)	11.676*** (1.006)
as.factor(region)Bryanskaya oblast	9.444*** (0.811)	2.025* (0.973)	8.393*** (1.001)	27.498*** (1.031)
as.factor(region)Čečenskaya Respublika	19.512*** (1.142)	40.313*** (1.381)	59.111*** (1.417)	61.451*** (1.430)
as.factor(region)Čelyabinskaya oblast	-0.849 (0.489)	-2.723*** (0.566)	-0.729 (0.605)	7.627*** (0.627)

Table 19: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Čukotskij avtonomnyj okrug	15.227*** (2.985)	19.890*** (3.421)	14.174*** (3.675)	15.301*** (3.827)
as.factor(region)Čuvašskaya Respublika - Čuvašiya	-0.855 (0.838)	2.426 (2.141)	5.077*** (1.037)	7.825*** (1.062)
as.factor(region)Evrejskaya avtonomnaya oblast	-0.887 (1.648)	-0.122 (1.891)	2.060 (2.030)	22.248*** (2.113)
as.factor(region)gorod Moskva	-4.030*** (0.550)		-1.983** (0.680)	3.508*** (0.700)
as.factor(region)gorod Sankt-Peterburg	-0.092 (0.565)		-6.634*** (0.699)	3.704*** (0.721)
as.factor(region)gorod Sevastopol	11.512*** (1.141)		12.524*** (1.406)	16.213*** (1.462)
as.factor(region)Habarovskij kraj	-3.444*** (0.844)	0.348 (1.028)	-4.087*** (1.043)	7.280*** (1.070)
as.factor(region)Irkutskaya oblast	-10.435*** (0.668)	-5.328*** (0.809)	-9.450*** (0.826)	-1.585 (0.849)
as.factor(region)Ivanovskaya oblast	-11.405*** (0.762)	-2.201* (0.937)	-8.755*** (0.941)	-3.174** (0.967)
as.factor(region)Kabardino-Balkarskaya Respublika	26.305*** (1.232)	16.600*** (1.518)	54.028*** (1.522)	51.587*** (1.556)
as.factor(region)Kaliningradskaya oblast	-6.549*** (0.790)	-3.744*** (0.966)	-0.147 (0.977)	5.118*** (1.003)
as.factor(region)Kalužskaya oblast	-1.244 (0.858)		-3.690*** (1.061)	4.387*** (1.088)
as.factor(region)Kamčatskij kraj	3.850*** (0.999)	2.890* (1.141)	0.882 (1.231)	4.604*** (1.275)

Table 19: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Karačaevsko-Čerkesskaya Respublika	22.399*** (1.439)	29.687*** (1.739)	57.249*** (1.776)	53.136*** (1.826)
as.factor(region)Kemerovskaya oblast - Kuzbass				35.331*** (0.800)
as.factor(region)Kirovskaya oblast	-6.830*** (0.716)	-0.0005 (0.862)	-3.373*** (0.885)	4.322*** (0.911)
as.factor(region)Kostromskaya oblast	-6.410*** (0.875)	-1.667 (1.032)	-3.585*** (1.079)	-0.028 (1.116)
as.factor(region)Krasnoyarskij kraj	-7.013*** (0.565)	-4.789*** (0.664)	-7.897*** (0.698)	2.826*** (0.723)
as.factor(region)Krasnodarskij kraj	7.554*** (0.579)	1.172 (0.707)	1.745* (0.721)	20.300*** (0.737)
as.factor(region)Kurganskaya oblast	0.830 (0.869)	9.443*** (0.961)	15.218*** (1.072)	4.938*** (1.039)
as.factor(region)Kurskaya oblast	1.197 (0.673)	3.433*** (0.781)	7.589*** (0.830)	-0.176 (0.861)
as.factor(region)Leningradskaya oblast	-1.450* (0.689)	1.585 (0.811)	-0.047 (0.855)	2.935*** (0.878)
as.factor(region)Lipeckaya oblast	-0.773 (4.469)		6.263 (5.503)	26.363*** (5.720)
as.factor(region)Magadanskaya oblast	7.797*** (1.487)	-1.307 (1.710)	3.148 (1.832)	-3.944* (1.906)
as.factor(region)Moskovskaya oblast	-2.983*** (0.500)	-3.604*** (0.595)	-4.288*** (0.620)	6.921*** (0.639)
as.factor(region)Murmanskaya oblast	-2.041** (0.726)	-2.517** (0.860)	-4.560*** (0.895)	-1.331 (0.923)

Table 19: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Neneckij avtonomnyj okrug	-0.471 (2.674)	5.286 (3.064)	6.933* (3.292)	4.932 (2.948)
as.factor(region)Nižegorodskaya oblast	-2.251*** (0.544)	7.267*** (0.663)	-1.336* (0.671)	4.305*** (0.694)
as.factor(region)Novgorodskaya oblast	-11.541*** (0.844)	-1.347 (1.656)	-6.268*** (1.041)	0.547 (1.078)
as.factor(region)Novosibirskaya oblast	-7.591*** (0.656)	-0.055 (0.787)	-8.251*** (0.811)	-1.215 (0.835)
as.factor(region)Omskaya oblast	-6.122*** (0.576)	0.581 (0.668)	-5.498*** (0.711)	0.818 (0.737)
as.factor(region)Orenburgskaya oblast	-2.290*** (0.590)	-3.435*** (0.690)	-5.329*** (0.729)	2.389** (0.756)
as.factor(region)Orlovskaya oblast	-1.443 (0.824)	4.749*** (0.963)	3.017** (1.018)	4.139*** (1.052)
as.factor(region)Penzenskaya oblast	5.833*** (0.622)	4.971*** (0.716)	11.896*** (0.767)	11.491*** (0.796)
as.factor(region)Permskij kraj	-3.663*** (0.632)	-12.473*** (0.832)	-9.729*** (0.786)	-1.587* (0.804)
as.factor(region)Primorskij kraj	-6.712*** (0.571)	0.862 (0.731)	-9.033*** (0.708)	1.310 (0.729)
as.factor(region)Pskovskaya oblast	0.559 (0.779)	0.238 (0.895)	2.278* (0.961)	6.485*** (0.998)
as.factor(region)Ryazanskaya oblast	-3.801*** (0.725)	1.026 (0.847)	-1.346 (0.897)	5.905*** (0.922)
as.factor(region)Respublika Adygeya (Adygeya)	-1.099 (1.460)	8.770*** (1.788)	5.858** (1.809)	23.500*** (1.847)

Table 19: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Respublika Altaj	-5.495* (2.152)	4.221 (2.555)	1.503 (2.654)	6.775* (2.741)
as.factor(region)Respublika Baškortostan	4.283*** (0.887)	10.385*** (1.131)	25.525*** (1.100)	28.960*** (1.113)
as.factor(region)Respublika Buryatiya	10.476*** (1.057)	14.421*** (1.310)	-0.937 (1.306)	7.939*** (1.339)
as.factor(region)Respublika Dagestan	17.258*** (1.033)	30.809*** (1.272)	49.498*** (1.273)	49.309*** (1.306)
as.factor(region)Respublika Hakasiya	-3.070** (1.062)	0.632 (1.278)	-4.132** (1.310)	-1.757 (1.348)
as.factor(region)Respublika Inguşetiya				47.931*** (1.944)
as.factor(region)Respublika Kalmykiya	2.915 (1.557)	3.768* (1.885)	18.327*** (1.921)	11.044*** (1.974)
as.factor(region)Respublika Kareliya	-6.922*** (1.113)	-4.200** (1.411)	2.202 (1.375)	3.182* (1.406)
as.factor(region)Respublika Komi	-8.204*** (1.050)	8.417*** (1.300)	-1.070 (1.298)	-0.228 (1.325)
as.factor(region)Respublika Krym	8.612*** (1.545)		12.009*** (1.906)	13.295*** (1.980)
as.factor(region)Respublika Marij Él	-3.346** (1.087)	7.101*** (1.326)	10.413*** (1.342)	5.755*** (1.377)
as.factor(region)Respublika Mordoviya	2.982** (1.032)	32.424*** (1.251)	38.506*** (1.275)	21.329*** (1.310)
as.factor(region)Respublika Saha (yakutiya)	2.897** (1.000)	12.612*** (1.211)	1.531 (1.234)	10.847*** (1.269)

Table 19: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Respublika Severnaya Osetiya - Alaniya	23.271*** (1.045)	21.567*** (1.268)	47.236*** (1.290)	50.947*** (1.322)
as.factor(region)Respublika Tatarstan (Tatarstan)	9.025*** (0.487)	17.459*** (0.564)	33.945*** (0.602)	40.492*** (0.624)
as.factor(region)Respublika Tyva	23.642*** (1.517)	29.539*** (1.783)	46.094*** (1.871)	37.423*** (1.937)
as.factor(region)Rostovskaya oblast	-5.242*** (0.510)	0.452 (0.597)	0.702 (0.630)	2.315*** (0.653)
as.factor(region)Sahalinskaya oblast	-8.269*** (0.869)	-7.387*** (1.028)	-9.324*** (1.071)	-0.767 (1.115)
as.factor(region)Samarskaya oblast	-3.282*** (0.603)	6.734*** (1.932)	3.205*** (0.765)	3.597*** (0.768)
as.factor(region)Saratovskaya oblast	-2.002 (1.239)	5.413*** (1.426)	24.356*** (1.527)	3.359* (1.602)
as.factor(region)Smolenskaya oblast	-5.463*** (0.668)	-4.189*** (0.766)	-5.432*** (0.825)	-0.404 (0.852)
as.factor(region)Stavropol'skij kraj	8.865*** (0.792)	2.686** (0.975)	1.357 (0.979)	32.200*** (1.002)
as.factor(region)Sverdlovskaya oblast	-3.970*** (0.507)	-6.371*** (0.592)	-2.317*** (0.626)	11.730*** (0.649)
as.factor(region)Tambovskaya oblast	1.818** (0.697)	8.128*** (0.800)	-0.329 (0.862)	17.844*** (0.890)
as.factor(region)Tomskaya oblast	-2.181*** (0.643)	-1.248 (0.737)	-4.414*** (0.794)	6.484*** (0.824)
as.factor(region)Tulskaya oblast	0.333 (0.647)		-3.030*** (0.798)	11.881*** (0.827)

Table 19: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Tûmenskaya oblast	9.084*** (0.721)	21.542*** (1.648)	34.714*** (0.893)	19.642*** (0.918)
as.factor(region)Tverskaya oblast	-6.149*** (0.605)	-2.526*** (0.698)	2.513*** (0.746)	2.533** (0.775)
as.factor(region)Udmurtskaya Repùblika	-7.724*** (1.749)	0.313 (2.058)	1.428 (2.155)	7.621*** (2.228)
as.factor(region)Ulyanovskaya oblast	-10.724*** (0.743)		-5.132*** (0.958)	-5.325*** (0.950)
as.factor(region)Vladimirskaya oblast	-1.909** (0.739)	-9.035*** (0.895)	-4.581*** (0.913)	-0.260 (0.939)
as.factor(region)Volgogradskaya oblast	0.216 (0.599)	-2.230** (0.706)	-1.866* (0.740)	26.267*** (0.766)
as.factor(region)Vologodskaya oblast	0.080 (0.684)	-1.886* (0.805)	-2.845*** (0.846)	6.551*** (0.875)
as.factor(region)Voronežskaya oblast	-6.963*** (0.709)	-0.133 (0.880)	0.096 (0.878)	5.469*** (0.897)
as.factor(region)Zabajkalskij kraj	-9.747*** (0.974)	-2.377 (1.319)	-6.760*** (1.205)	-1.371 (1.238)
uik_population	-0.001*** (0.00005)	-0.0004*** (0.0001)	-0.001*** (0.0001)	-0.002*** (0.0001)
proximity:market_dum	-0.499* (0.245)	0.361 (0.377)	-0.572 (0.303)	-0.475 (0.307)
Observations	31,999	24,539	31,439	33,564
R <sup>2</sup>	0.369	0.385	0.587	0.573
Adjusted R <sup>2</sup>	0.260	0.269	0.517	0.502

Table 20: Regression results with market state ownership share interaction (market share  $\leq 50\%$ )

	Dependent variable:			
	Pres 2018 (1)	Pres 2012 (2)	Parl 2016 (3)	Parl 2021 (4)
proximity	1.875*** (0.140)	1.276*** (0.194)	2.945*** (0.173)	2.784*** (0.174)
market_dum_1	-0.555 (0.542)	0.378 (0.877)	0.231 (0.673)	1.009 (0.686)
as.factor(region)Yamalo-Neneckij avtonomnyj okrug	25.868*** (0.848)	36.017*** (3.439)	29.917*** (1.048)	26.535*** (1.085)
as.factor(region)Amurskaya oblast	-8.540*** (0.919)	3.766** (1.221)	-1.925 (1.134)	-0.565 (1.167)
as.factor(region)Arhangelskaya oblast	-6.691*** (0.839)	-3.395*** (1.010)	-5.882*** (1.042)	3.346** (1.064)
as.factor(region)Yaroslavskaya oblast				-0.920 (0.879)
as.factor(region)Astrahanskaya oblast	-7.174*** (1.011)	-3.912** (1.319)	-3.541** (1.248)	6.358*** (1.289)
as.factor(region)Belgorodskaya oblast	-1.310 (0.794)	9.697*** (0.963)	10.797*** (0.981)	11.656*** (1.006)
as.factor(region)Bryanskaya oblast	9.389*** (0.811)	1.995* (0.974)	8.370*** (1.001)	27.463*** (1.031)
as.factor(region)Čečenskaya Respublika	19.443*** (1.142)	40.280*** (1.381)	59.079*** (1.417)	61.401*** (1.430)
as.factor(region)Čelyabinskaya oblast	-0.856 (0.489)	-2.731*** (0.566)	-0.743 (0.605)	7.608*** (0.626)
as.factor(region)Čukotskij avtonomnyj okrug	15.244*** (2.984)	19.853*** (3.421)	14.204*** (3.675)	15.299*** (3.826)

Table 20: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Čuvaškaya Respublika - Čuvašiya	-0.903 (0.838)	2.372 (2.141)	5.058*** (1.037)	7.804*** (1.062)
as.factor(region)Evrejskaya avtonomnaya oblast	-0.907 (1.648)	-0.083 (1.890)	2.041 (2.030)	22.243*** (2.113)
as.factor(region)gorod Moskva	-4.070*** (0.550)		-1.997** (0.680)	3.505*** (0.700)
as.factor(region)gorod Sankt-Peterburg	-0.044 (0.566)		-6.624*** (0.699)	3.687*** (0.721)
as.factor(region)gorod Sevastopol	11.547*** (1.135)		12.629*** (1.398)	16.211*** (1.454)
as.factor(region)Habarovskij kraj	-3.502*** (0.844)	0.316 (1.028)	-4.113*** (1.044)	7.243*** (1.070)
as.factor(region)Irkutskaya oblast	-10.491*** (0.669)	-5.346*** (0.809)	-9.480*** (0.826)	-1.613 (0.849)
as.factor(region)Ivanovskaya oblast	-11.447*** (0.762)	-2.230* (0.937)	-8.770*** (0.941)	-3.201*** (0.967)
as.factor(region)Kabardino-Balkarskaya Respublika	26.195*** (1.232)	16.592*** (1.519)	53.978*** (1.522)	51.548*** (1.556)
as.factor(region)Kalininogradskaya oblast	-6.582*** (0.790)	-3.760*** (0.966)	-0.158 (0.977)	5.110*** (1.003)
as.factor(region)Kalužskaya oblast	-1.260 (0.858)		-3.699*** (1.061)	4.395*** (1.088)
as.factor(region)Kamčatskij kraj	3.841*** (0.999)	2.879* (1.141)	0.874 (1.231)	4.580*** (1.275)
as.factor(region)Karačaevsko-Čerkesskaya Respublika	22.288*** (1.439)	29.679*** (1.739)	57.212*** (1.776)	53.112*** (1.826)

Table 20: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Kemerovskaya oblast - Kuzbass				35.320*** (0.800)
as.factor(region)Kirovskaya oblast	-6.856*** (0.715)	-0.003 (0.862)	-3.389*** (0.885)	4.313*** (0.911)
as.factor(region)Kostromskaya oblast	-6.410*** (0.875)	-1.652 (1.032)	-3.569*** (1.079)	0.006 (1.116)
as.factor(region)Krasnoyarskij kraj	-7.050*** (0.565)	-4.794*** (0.664)	-7.918*** (0.698)	2.807*** (0.723)
as.factor(region)Krasnodarskij kraj	7.557*** (0.579)	1.181 (0.707)	1.752* (0.721)	20.321*** (0.737)
as.factor(region)Kurganskaya oblast	0.805 (0.869)	9.418*** (0.961)	15.215*** (1.072)	4.927*** (1.039)
as.factor(region)Kurskaya oblast	1.155 (0.673)	3.421*** (0.781)	7.561*** (0.830)	-0.208 (0.861)
as.factor(region)Leningradskaya oblast	-1.467* (0.689)	1.568 (0.811)	-0.053 (0.855)	2.919*** (0.878)
as.factor(region)Lipeckaya oblast	-0.888 (4.468)		6.161 (5.503)	26.255*** (5.718)
as.factor(region)Magadanskaya oblast	7.708*** (1.487)	-1.337 (1.710)	3.082 (1.832)	-4.031* (1.905)
as.factor(region)Moskovskaya oblast	-2.994*** (0.500)	-3.610*** (0.595)	-4.305*** (0.620)	6.902*** (0.639)
as.factor(region)Murmanskaya oblast	-2.099** (0.726)	-2.575** (0.861)	-4.600*** (0.895)	-1.414 (0.923)
as.factor(region)Neneckij avtonomnyj okrug	-0.531 (2.673)	5.227 (3.064)	6.870* (3.293)	4.848 (2.948)

Table 20: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Nižegorodskaya oblast	-2.278*** (0.543)	7.268*** (0.663)	-1.354* (0.671)	4.294*** (0.694)
as.factor(region)Novgorodskaya oblast	-11.570*** (0.844)	-1.402 (1.656)	-6.282*** (1.041)	0.524 (1.077)
as.factor(region)Novosibirskaya oblast	-7.590*** (0.656)	-0.077 (0.787)	-8.248*** (0.811)	-1.225 (0.835)
as.factor(region)Omskaya oblast	-6.129*** (0.576)	0.607 (0.667)	-5.511*** (0.711)	0.822 (0.737)
as.factor(region)Orenburgskaya oblast	-2.300*** (0.590)	-3.412*** (0.690)	-5.335*** (0.729)	2.404** (0.756)
as.factor(region)Orlovskaya oblast	-1.498 (0.824)	4.715*** (0.963)	2.986** (1.018)	4.088*** (1.052)
as.factor(region)Penzenskaya oblast	5.824*** (0.622)	4.990*** (0.716)	11.898*** (0.767)	11.511*** (0.796)
as.factor(region)Permskij kraj	-3.704*** (0.632)	-12.499*** (0.832)	-9.758*** (0.786)	-1.600* (0.804)
as.factor(region)Primorskij kraj	-6.735*** (0.571)	0.874 (0.731)	-9.047*** (0.708)	1.296 (0.729)
as.factor(region)Pskovskaya oblast	0.526 (0.779)	0.215 (0.895)	2.252* (0.961)	6.441*** (0.998)
as.factor(region)Ryazanskaya oblast	-3.870*** (0.725)	1.010 (0.847)	-1.399 (0.897)	5.850*** (0.922)
as.factor(region)Respublika Adygaea (Adygeya)	-1.182 (1.461)	8.729*** (1.789)	5.840** (1.809)	23.488*** (1.847)
as.factor(region)Respublika Altaj	-5.578** (2.152)	4.147 (2.555)	1.497 (2.654)	6.746* (2.740)

Table 20: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Respublika Baškortostan	4.200*** (0.887)	10.411*** (1.131)	25.485*** (1.100)	28.954*** (1.113)
as.factor(region)Respublika Buryatiya	10.405*** (1.057)	14.449*** (1.310)	-0.962 (1.306)	7.944*** (1.339)
as.factor(region)Respublika Dagestan	17.170*** (1.033)	30.777*** (1.272)	49.464*** (1.273)	49.280*** (1.306)
as.factor(region)Respublika Hakasiya	-3.162** (1.062)	0.580 (1.278)	-4.185** (1.311)	-1.836 (1.348)
as.factor(region)Respublika Inguşetiya				47.957*** (1.944)
as.factor(region)Respublika Kalmykiya	2.822 (1.557)	3.667 (1.886)	18.318*** (1.922)	11.006*** (1.975)
as.factor(region)Respublika Kareliya	-7.004*** (1.113)	-4.242** (1.411)	2.151 (1.375)	3.113* (1.406)
as.factor(region)Respublika Komi	-8.274*** (1.050)	8.386*** (1.300)	-1.098 (1.298)	-0.262 (1.325)
as.factor(region)Respublika Krym	8.847*** (1.544)		12.155*** (1.905)	13.330*** (1.978)
as.factor(region)Respublika Marij Él	-3.415** (1.087)	7.056*** (1.327)	10.385*** (1.343)	5.710*** (1.377)
as.factor(region)Respublika Mordoviya	2.914** (1.032)	32.404*** (1.251)	38.473*** (1.276)	21.289*** (1.310)
as.factor(region)Respublika Saha (yakutiya)	2.852** (1.000)	12.622*** (1.211)	1.518 (1.234)	10.852*** (1.269)
as.factor(region)Respublika Severnaya Osetiya - Alaniya	23.192*** (1.045)	21.537*** (1.268)	47.196*** (1.290)	50.896*** (1.322)

Table 20: (continued)

	Dependent variable:			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Respublika Tatarstan (Tatarstan)	9.028*** (0.487)	17.454*** (0.564)	33.945*** (0.602)	40.489*** (0.623)
as.factor(region)Respublika Tyva	23.572*** (1.517)	29.497*** (1.783)	46.072*** (1.871)	37.389*** (1.936)
as.factor(region)Rostovskaya oblast	-5.261*** (0.510)	0.451 (0.597)	0.693 (0.631)	2.310*** (0.653)
as.factor(region)Sahalinskaya oblast	-8.249*** (0.869)	-7.356*** (1.028)	-9.312*** (1.071)	-0.737 (1.115)
as.factor(region)Samarskaya oblast	-3.304*** (0.603)	6.741*** (1.932)	3.202*** (0.765)	3.613*** (0.768)
as.factor(region)Saratovskaya oblast	-2.021 (1.237)	5.185*** (1.420)	24.418*** (1.524)	3.357* (1.599)
as.factor(region)Smolenskaya oblast	-5.479*** (0.668)	-4.199*** (0.766)	-5.445*** (0.825)	-0.425 (0.852)
as.factor(region)Stavropol'skij kraj	8.812*** (0.792)	2.658** (0.975)	1.333 (0.979)	32.166*** (1.002)
as.factor(region)Sverdlovskaya oblast	-4.014*** (0.507)	-6.376*** (0.592)	-2.347*** (0.626)	11.701*** (0.649)
as.factor(region)Tambovskaya oblast	1.799** (0.697)	8.110*** (0.800)	-0.340 (0.862)	17.819*** (0.890)
as.factor(region)Tomskaya oblast	-2.222*** (0.643)	-1.264 (0.737)	-4.455*** (0.793)	6.431*** (0.824)
as.factor(region)Tulskaya oblast	0.305 (0.647)		-3.055*** (0.798)	11.845*** (0.827)
as.factor(region)Tümenskaya oblast	9.041*** (0.721)	21.546*** (1.647)	34.694*** (0.893)	19.614*** (0.918)

Table 20: (continued)

	<i>Dependent variable:</i>			
	Putin 2018 (1)	Putin 2012 (2)	UR 2016 (3)	UR 2021 (4)
as.factor(region)Tverskaya oblast	-6.201*** (0.605)	-2.520*** (0.698)	2.468*** (0.746)	2.490** (0.775)
as.factor(region)Udmurtskaya Respublika	-7.770*** (1.748)	0.308 (2.058)	1.440 (2.155)	7.664*** (2.228)
as.factor(region)Ulyanovskaya oblast	-10.747*** (0.743)		-5.153*** (0.958)	-5.341*** (0.950)
as.factor(region)Vladimirskaya oblast	-1.964** (0.739)	-9.054*** (0.895)	-4.606*** (0.913)	-0.289 (0.939)
as.factor(region)Volgogradskaya oblast	0.209 (0.599)	-2.248** (0.706)	-1.865* (0.740)	26.266*** (0.766)
as.factor(region)Vologodskaya oblast	0.024 (0.684)	-1.908* (0.805)	-2.892*** (0.846)	6.490*** (0.875)
as.factor(region)Voronežskaya oblast	-7.017*** (0.709)	-0.146 (0.880)	0.068 (0.878)	5.442*** (0.897)
as.factor(region)Zabajkalskij kraj	-9.769*** (0.974)	-2.408 (1.319)	-6.751*** (1.206)	-1.341 (1.238)
uik_population	-0.001*** (0.00005)	-0.0004*** (0.0001)	-0.001*** (0.0001)	-0.002*** (0.0001)
proximity:market_dum_1	-0.085 (0.367)	-0.634 (0.571)	-0.466 (0.456)	-1.232** (0.463)
Observations	31,999	24,539	31,439	33,564
R <sup>2</sup>	0.369	0.385	0.587	0.573
Adjusted R <sup>2</sup>	0.260	0.269	0.517	0.502

Note:

\*p&lt;0.05; \*\*p&lt;0.01; \*\*\*p&lt;0.001

# Friends with benefits: exploring donors of the Russian ruling party

## Abstract

Why do private companies contribute to the ruling party in an authoritarian regime? While part of the motivation may align with democratic logic, involving both ideological and opportunistic strategies of support, non-democratic regimes introduce additional factors into this dynamic. This results in a more direct and widespread manifestation of corruption, particularly in sectors of specific interest to autocrats. This paper delves into the donations made by private companies to United Russia party from 2011 to 2022. Specifically, it presents evidence suggesting that a one-time contribution to United Russia by major business entities increases the value of contracts awarded to the company, particularly in two economic sectors. In contrast, regular contributions do not have the same significant impact on returns from public procurement contracts, differentiating ideological supporters from opportunistic ones.

## 1 Introduction

What characterizes the relationship between the dominant party and its donors in an authoritarian setting? While extensive literature on party donors typically explores their influence in mature democracies like the United States or the United Kingdom, there is a lack of information on these dynamics in less studied non-democratic contexts. This scarcity is primarily attributable to limitations in data availability and reporting regulations, coupled with the overall reliance of political parties on private donations. For instance, in the UK, the two major parties derive less than 15% of their funds from public sources, with the remainder originating from membership fees and donations (Barr et al., 2020). In the United States, candidates from both the Republican and Democratic parties fund their entire electoral campaigns through private donations, with only a small fraction coming from self-funding (Federal Election Committee, n.d.). Understanding information about donors becomes crucial in shaping the agenda for electoral campaigns in these countries. However, democratic systems still grapple with challenges arising from private donations to parties, including concerns related to corruption and inequality (Birch, 2022).

Although it is evident why politicians depend on private donations—these funds are necessary for electoral campaigns and party operations—the rationale behind donors is more intricate and extensively studied. Donors, particularly significant contributors, strategically decide on their donations (Brown, 2013), often wielding the potential to influence legislative outcomes with financial support (Powell, 2012), gain economic benefits (Titl & Geys, 2019),

lobby corporate interests (Acton & Hawkins, 2022), or in general contribute to various forms of corruption (Fisher, 1994). Individual donors may have different perspectives on their motives compared to corporate ones. For instance, (Barber, 2016) demonstrated that individual donations are primarily ideological, while political action committees aim for access and influence through their contributions. In Canada, where private donations are capped and constitute one of two party income sources, Garnett et al., 2022 identified two types of motivation: generalized support and transactional support, with ideological support being more prevalent among smaller or individual donors.

Therefore, in democracies, the motivation behind donations depends on the type of support offered to individual politicians or parties, distinguishing between ideology-based support and reciprocity-anticipation support (Powell et al., 2003), which could also involve either access or influence, as highlighted by Barber, 2016. While ideological support is present in both democracies and autocracies with similar underlying mechanisms (Geddes & Zaller, 1989; Mauk, 2017, 2020), reciprocity-anticipation support or opportunistic support in autocracies is likely to manifest in different ways.

Due to the transparency and accountability mechanisms in place, corruption in democratic countries is, on average, less wide-spread than in autocracies (Gerring & Thacker, 2004; Hollyer & Wantchekon, 2015; Kunicova & Rose-Ackerman, 2005). Authoritarian systems often lack grand corruption prevention mechanisms (Rose-Ackerman, 1996), which instruments like corporate donations sometimes attempt to overcome in democracies. Hence, it can be anticipated that in an authoritarian setup characterized by state capture and heightened levels of corruption, donating money to politicians may not be necessary for achieving private gains. Yet such practices persist.

The motivation behind party donations in authoritarian settings also differs due to the absence of party competition. In democracies, donations to political parties ultimately supply resources for them to compete and influence their electoral success (Brown, 2013). In authoritarian regimes, election outcomes are typically highly predictable, and competition in donations has limited impact on the results. This raises the question: why do private companies contribute to the dominant party in an authoritarian regime?

This article examines donors of the United Russia party from 2011 to 2022. We argue that the relationship between donors and the dominant Russian party follows a logic similar to donors in democracies, revealing both ideological and "investment" strategies. However, due to the nature of the regime, the investment leads to direct corrupt exchanges involving returns from public funds. Through an analysis of donors' involvement in public procurement, we discovered evidence suggesting that contributing money to United Russia by large business actors increases the value of contracts won by a company, resembling the behavior of an opportunistic donor as opposed to an ideological supporter. Furthermore, this effect appears to be particularly pronounced in sectors that can prove useful to the dominant party.

## 2 Business actors support in authoritarian regimes

Some authors claim that the nature of business cooperation with political parties in non-democratic environments is in mutually beneficial exchange, while others argue that the relationship is more unilateral. As it is demonstrated in the comparative studies of economy

of non-democratic states, business actors in competitive authoritarian setting are subject to constant renegotiation of the terms of business-state relations (Sallai & Schnyder, 2021), which causes a lot of uncertainty and limits business ability for innovations (Wang et al., 2021) or getting private investments (Gehlbach & Keefer, 2012) unless institutions restricting autocratic government are in place. Business relationships with state under dictatorship usually imply higher state dependency of economic actors, reduction of economic pluralism to align the interests of the business elite with those of the ruling elite, and the general use of the state to pursue the interests of the ruling elite (Sallai & Schnyder, 2021, p.1340). Such an approach views economic actors as dependent on the state and does not allow economic elites much room for maneuver. Esen and Gumuscu, 2018 showed that in order to consolidate its support in business circles, Turkey's ruling party AKP took a number of measures, such as politicizing state bureaucracy, weakening judicial oversight, and undermining the rule of law. The authors state that such measures were taken for the sake of channeling public resources from the ruling party to its supporters through patronage. In addition, it allowed to transfer capital from opponents to cronies and discipline dissidents within business circles. These actions have tilted the playing field in favor of the AKP by giving pro-AKP businessmen access to private resources, campaign contributions, and media support.

However, viewing business actors as mere "hostages" of the regime oversimplifies the reality. Business actors may appreciate or even take steps to undermine the country's legal or political system in cases where the state's economy is predominantly rent-seeking. As demonstrated by El Tarouty, 2016 in the case of Mubarak's Egypt, business actors often opt to align with an authoritarian regime in pursuit of their own economic advantages. In Indonesia high-level businessmen support attempts to reduce the Corruption Eradication Commission's institutional powers to assure possibility to extract rent (Mudhoffir & A'yun, 2021). Support for system features typical of authoritarian settings often goes hand in hand with political cooptation, especially when business actors are interested in lobbying for their own interests. The Chinese example of state-business relations shows that collusive relations between business and politics or informal ties with local governments are more likely to produce favorable outcomes for business in lobbying for its interests (Huang & Chen, 2020).

The very nature of the regime does not allow for independent economic competition and tends to involve various forms of corruption for business actors to gain profit. Furthermore, it appears that both parties are more likely to gain significantly when closely cooperating. Dosal, 1993 illustrated this point through the example of the American company "United Fruit," which strategically engaged with dictators in Guatemala. This collaboration provided the company with the opportunity to monopolize the banana business and railroad network, often in exchange for bribes. The argument is made that under democratic institutions, this level of economic success would not have been achievable for the company. Similarly, the construction sector in Spain during Franco's dictatorship greatly benefited from existing political repressions, gaining access to prison labor (Gonzalo, 2013). This addressed the issue of workforce shortages for state infrastructural or military tasks. The economic transformation initiated by the Pinochet regime, including privatizations, led to the concentration of wealth in a small number of economic groups, redistributing the state's wealth to elites (Huneeus & Undurraga, 2021).

In general, robust economic performance becomes crucial for the survival of the regime, particularly for securing the support of ruling elites or redistributing benefits among core

supporters (Arias et al., 2018; Bak & Moon, 2016; De Mesquita et al., 2005; Wintrobe, 2000). Furthermore, dictatorships can leverage businesses for regime survival in various ways beyond mere economic prosperity. This includes utilizing labor to mobilize political support (Frye et al., 2014; Kim & Gandhi, 2010), engaging in patronage (Gomez & Jomo, 1999; Hadiz & Robison, 2004), or utilizing returns from grand corruption for clientelism (Singer, 2009).

The degree to which a regime seeks to co-opt its economic actors for political gains, as well as the means to use for that can vary depending on the sector. Certain sectors, such as natural resource extraction industries, may be utilized for gaining profit into state budget (Jensen & Wantchekon, 2004; van der Ploeg, 2011), or for more direct rent extraction (Dorsch & Maarek, 2018). On the other hand, other sectors can contribute to the provision of visible public goods by the government (Mani & Mukand, 2007) and aid in garnering popular support. In this study, it is presumed that business actors are aware of the regime's intentions to instrumentalize them and comply with the rules set by the regime to extract profits. This assumption stems from the mutual interests inherent in business-state relationships within a dictatorship.

While the regime aims to acquire resources to maintain its power, businesses seek to gain profits, leading to their collaboration. It is expected that the dynamics of relationships between the state apparatus and the private sector in competitive authoritarianism differ based on the type of business actors but generally follow mutually beneficial rent-extracting patterns. We anticipate the following determinants to explain heterogeneity in cooperation between the state and businesses in autocracy.

Firstly, it is expected that the size of the company influences the potential for businesses to derive extra profits from collaborating with the state and participating in rent-seeking exchanges. While small and medium businesses are likely to face and struggle with increased corruption and a high level of uncertainty (Yadav & Mukherjee, 2016), it is large businesses that capture the interest of autocrats the most (Basualdo et al., 2020, 2021; Bogliaccini et al., 2021). Large businesses enable regimes to implement ambitious infrastructure projects through major construction companies, as observed in the case of Brazil under the military regime (Basualdo et al., 2020; Pedreira Campos, 2021). They also allow for the distribution of rent among selected business elites without the need to redistribute it among many, as seen in Pinochet's Peru (Huneeus & Undurraga, 2021). Additionally, having major industries under control ensures they are not, for example, unionizing (Stillerman, 2003), which is important for control over potential political opponents. Certainly, in dictatorships, the state often finds it necessary to partially suppress large businesses to ensure they align with the state's interests and do not shift their loyalty. This strategy was notably employed by Vladimir Putin at the beginning of his presidential term with Russian oligarchs (Sakwa, 2014; Sixsmith, 2010), as well as by Recep Erdogan in Turkey (Esen & Gumuscu, 2018). Forming alliances with big businesses, using both rewards and punishments, provides the state with essential resources but demands a willingness to share those resources as well.

Secondly, specific sectors of companies typically engage in collaboration with the state under dictatorship. Similar to the interest in large businesses, autocratic regimes require resources to maintain political stability. Consequently, their interest in particular sectors depends on profitability and usefulness for other subjective goals of the ruling elites. For instance, autocracies that benefit the most from food production are more likely to witness

collaboration between the state and major agricultural companies, as seen in Guatemala (Dosal, 1993). Meanwhile, regimes dependent on natural resource extraction tend to coopt this sector first, as observed with the steel industry in Argentina (Basualdo et al., 2020). In addition to acquiring resources and ensuring enrichment for themselves and their elites, autocrats also engage in redistribution (Wintrobe, 2000). They often require resources for some inefficient yet politically advantageous social policies or infrastructure projects aimed at securing popular support (Diaz-Cayeros et al., 2016). Consequently, sectors such as construction appear to be particularly corrupt and of significant interest to many autocrats, including Franco (Gonzalo, 2013), Orban (Fazekas et al., 2015), or the military junta in Brazil (Pedreira Campos, 2021).

Lastly, it is unreasonable to assume that certain businesses may not be interested in collaborating with or supporting the state due to ideological alignment. Nazi Germany stands as a prominent example of the ideological support businesses provided to Hitler's regime (Nicosia & Huener, 2004). As demonstrated by Basualdo, 2021, the Argentinian dictatorship of 1976-1983 was characterized by ideological alignment between businesses and the military. Such support could hinge on the access that the state provides to businesses in the decision-making process, as long as this influence persists, as was the case with business elites in Pinochet's Chile (Silva, 2019). In any scenario, akin to corporate support in democracies, collaboration between business and state in dictatorships can stem from either ideological or opportunistic motives. The conceptual distinction between the two is grounded in the anticipated outcomes of such support. Ideological support anticipates policies aligned with shared values, while opportunistic support expects more tangible, materialistic returns (Barber, 2016).

### 3 Party resources

This research proposes to examine the nature of business support for authoritarian states through corporate donations received by the dominant party. There are several reasons why this can serve as a valuable measurement. Firstly, authoritarian regimes often face challenges in assessing the "real" popular support due to restricted access to closed dictatorships by international researchers and pollsters (Guriev & Treisman, 2020). Additionally, the so-called "spiral of silence" (Noelle-Neumann & Petersen, 2004) prevails in autocracies, hindering people from expressing opinions they perceive as unsafe or potentially isolating (Kalinin, 2016). In this context, donations made to the dominant party can serve as a reliable proxy for measuring business support for the regime. Secondly, existing literature on authoritarianism often neglects the variation in types of resources involved in dominant party operations (Diaz-Cayeros et al., 2016, p.68-69), instead concentrating on the overall resource advantage (Greene, 2010), access to state resources (Schedler, 2006), or allocation of resources among the ruling elite (Boix & Svolik, 2013). Exploring donations could enhance this field of research by providing the opportunity to assess support in its heterogeneity. This includes examining the sectors in which a company-supporter operates, the resources this company possesses, its size, and its behavior towards the dominant party, such as the regularity of support.

This research centers on the dominant party as it holds significance within authoritarian

regimes. The dominant party plays a crucial role in enhancing regime stability through increased institutionalization, a characteristic often lacking in personalist dictatorships, making them more susceptible to collapse (Geddes et al., 2014). Furthermore, the dominant party addresses the credible commitment problem among political elites (Reuter & Remington, 2009). Given its functions of mediating, coopting, and distributing resources, the study focuses on resources of the dominant party by focusing at private donations. We contend that providing support to the dominant party ensures the distribution of benefits among elites and is motivated by factors distinct from those influencing support for the head of state (Sirotkina & Zavadskaya, 2020). These differences arise from variations in roles, public perception, and institutional foundations.

This article suggests that the mechanism of the party's financial inflow through donations from private companies has its routes in corrupt exchange, when companies are allowed to get access to public money through public procurement contracts in exchange for financial support to the party. It is anticipated that there will be significant heterogeneity in public procurement outcomes based on three dimensions reflecting key company characteristics and donation behavior. First, two types of dominant party support are expected: ideological and opportunistic. Ideological support is less likely to yield significant economic benefits for the company and is anticipated to be less common, while opportunistic support is expected to result in substantial returns through public procurement contracts. Secondly, there is an expectation of variation in public procurement returns across different sectors. Markets of particular interest to the autocrat, such as the construction sector, are expected to exhibit a higher proportion of opportunistic behavior from companies, resulting in greater returns in exchange for their support of the dominant party. Finally, variation is expected in the amount of returns the company receives from supporting the dominant party depending on its size. Larger companies in terms of revenue are expected to experience higher returns from donations due to their particular significance to the regime.

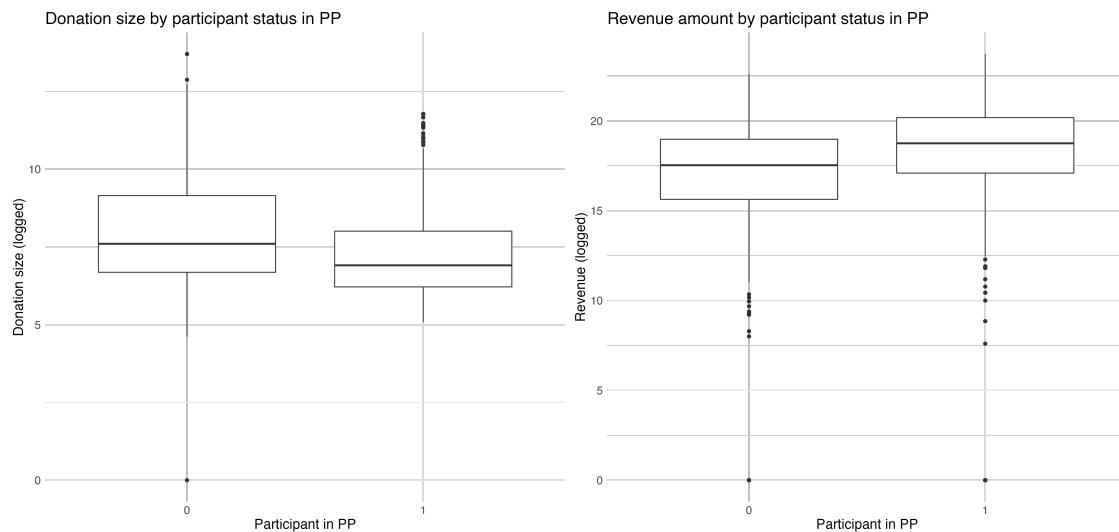
## 4 Description of Russian donors

Political parties in Russia receive funding from various sources, with the state budget serving as the primary financial contributor for most. According to the law<sup>1</sup>, parties are entitled to 152 RUB for each vote garnered in the latest parliamentary elections if they surpass the 3% threshold. Over the years, there has been noticeable variation among parties in the proportion of funding received from the state budget, corporate donations, and party membership fees. United Russia stands out not only as the wealthiest party, given its substantial number of votes compared to others, but also as one of the few parties with a significant share of corporate donations. For instance, in 2023, United Russia's share of state financing was below 50% (**anastasiyakornyaGosbyudzhetomEdiny**).

Approximately 30% of all United Russia donors secure government procurement contracts. As anticipated, larger companies are noted for having received state contracts (Figure 1, right side). However, the median value of donations is lower for companies involved in public procurement compared to those who are not (Figure 1, left side). The median

<sup>1</sup>Federal Law of Russian Federation of July 11, 2001 No. 95-FZ (as amended on July 24, 2023) "On Political Parties". Chapter VII. State Financing of Political Parties

**Figure 1:** Donor Revenue and Donation Amount Based on Public Procurement Participation

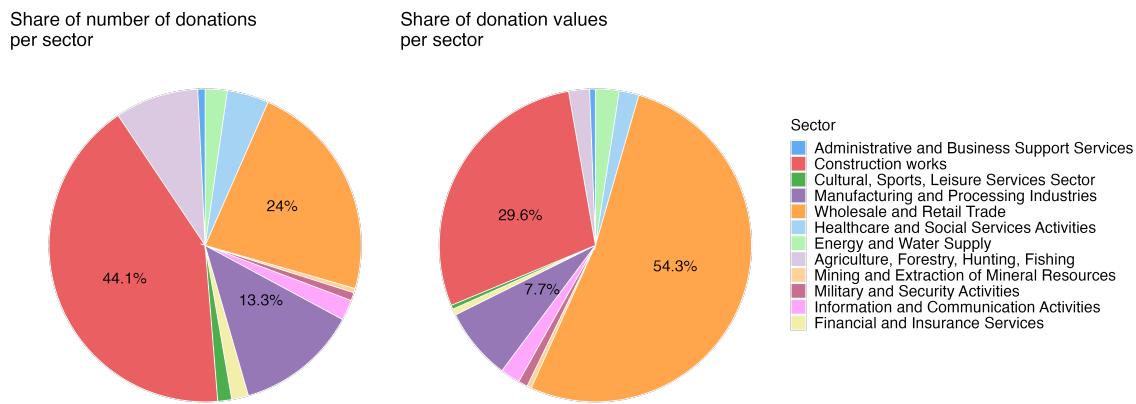


donation for donors participating in public procurement is 1,000,000 RUB, in contrast to 2,000,000 RUB for non-participants.

Figure 2 illustrates the distribution of donations in terms of both quantity and monetary value across various sectors. The three most prolific contributors in terms of the number of donations are the Construction sector, Wholesale and Retail Trade, and Manufacturing and Processing Industries, constituting 44%, 24%, and 13% of the total donations, respectively. The remaining sectors collectively share from 10% to 0.5% of the overall donors. Yet, upon scrutinizing the donation values, Wholesale and Retail Trade stands out as the most substantial contributor, representing over 54% of the total monetary value of donations, with an average donation amount of 2,3 billion RUB. The construction sector follows closely, holding a 30% share, and an average donation amount of 1,2 billion RUB. Manufacturing and Processing Industries contribute 8% to the overall value of donations received by United Russia, with an average donation amount of 330 million RUB.

The elevated donation amounts observed among companies not involved in public procurement may be attributed to a distinct organizational category that frequently appears as a donor for United Russia – non-profit organizations. These entities exclusively function as support funds for the party and are often registered at the same address as United Russia offices. Due to their non-profit status, tracing the origin of their funding proves particularly challenging. According to media investigations, these non-profit funds are linked to prominent figures such as Gennadiy Timchenko, Sergey Shoigu, and other influential businesspeople and politicians within the ruling elite (**occrpAnonimnayaShchedrostChto**). This form of financing became actively employed during the 2018 presidential campaign and was thought to be a strategy for circumventing sanctions, enabling companies to contribute funds without leaving public traces.

**Figure 2:** Share of Donation Numbers and Values Across Sectors



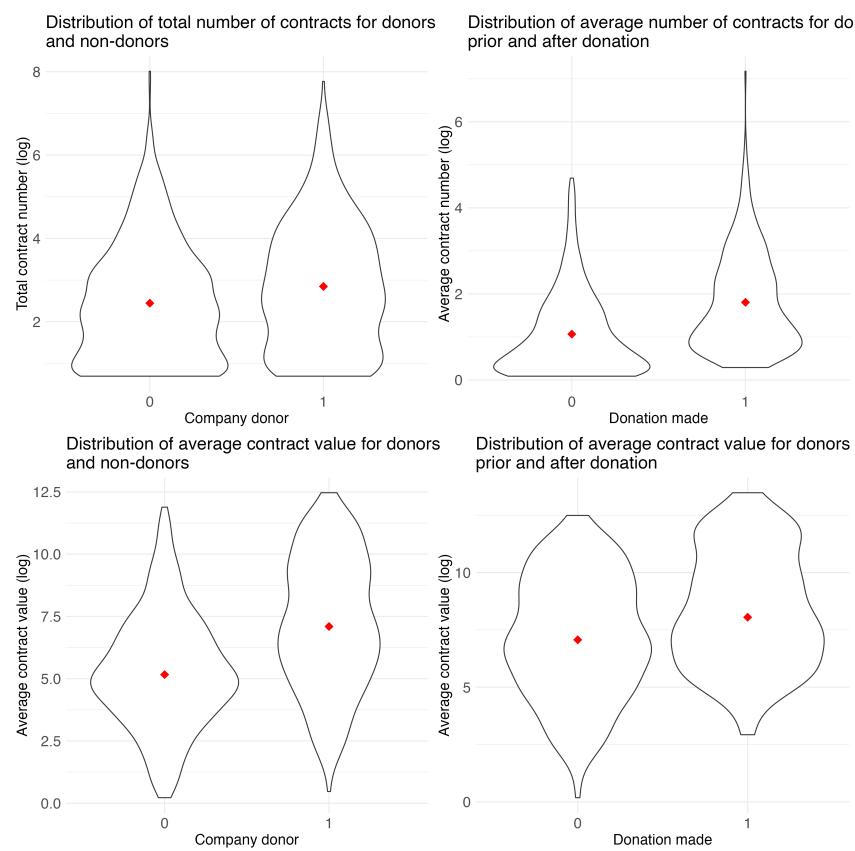
## 5 Event study design

This article employs an event study design to investigate the impact of donations to the United Russia party on the number and value of public contracts received by a firm. The issue of endogeneity arises when examining the relationship between donations and public procurement contracts at the company level. We operate under the assumption that the allocation of public procurement contracts is, to some extent, influenced by the company's decision to participate in bidding. However, we argue that the final decision is predominantly made by public officials and is based on external evaluation and judgment. Additionally, our analysis involves matching groups of companies with similar characteristics that participate in public procurement. The anticipation of the null hypothesis involves expecting no discernible differences between donors and non-donors if the outcome of public procurement primarily depends on company characteristics and the willingness to submit bids. Yet on contrary, descriptive statistics reveal significant distinctions between the two groups (Figure 3). This enables us to conclude that the allocation of public procurement is not influenced by the company's contributions to the dominant party and proceed with event study design<sup>2</sup>.

One of the other key challenges in this research is the timing of donations, which varies among different companies. To address this issue, the article utilizes the Sun and Abraham interaction, to prevent contamination by effects from other periods typical for two-way fixed effects regressions (TWFE) commonly used for such analyses (Sun & Abraham, 2021). The results for general model with the use of the Two-way Fixed Effects Counterfactual estimator, also known as the two-stage DiD (Borusyak et al., 2021; Butts & Gardner, 2021) are also

<sup>2</sup>For other works using event study where the event is partially within the unit's control see Molitor, 2018 on physicians' pattern of behavior as they move to new locations, Bechetti et al., 2009 on Corporate Social Responsibility and shareholder's value, Bechetti et al., 2009 on corporate entry and exit from the Domini 400 Social Index and consequential asset prices reaction

**Figure 3:** Violin plot: Average and total contract values for donors vs. non-donors (left) and donors who already made donations vs. those who haven't (right).



presented (Table 1 and 2).

The standard two-ways fixed effects with dynamic set-up the event study formula is presented below (Sun & Abraham, 2021):

$$Y_{i,t} = \alpha_i + \gamma_t + \sum_{l=-K}^{-2} \mu_l D_{i,t}^l + \sum_{l=0}^L \mu_l D_{i,t}^l + \nu_{i,t}$$

Where  $Y_{it}$  is the outcome variable for company-year,  $\alpha_i$  is the unit-specific fixed effect,  $\gamma_t$  is the time-specific fixed effect. The first summation term represents the effect of treatment leads ( $K$ ), where  $D_{i,t}^l$  is an indicator variable that equals 1 if unit  $i$  is  $l$  periods away from the initial treatment at time  $t$  and 0 otherwise. The coefficient  $\mu$  captures the impact of the donation in those lead periods. The second summation represents the effect of treatment lags ( $L$ ), with the coefficient  $\mu$  capturing the impact of the donation in lag periods. The model excludes relative periods  $-1$  to avoid multicollinearity in the model. The cohort-specific average treatment effect on the treated calculated as below:

$$CATT_{e,l} = E(Y_{i,e+l} - Y_{i,e+l}^\infty | E_i = e)$$

Where  $E_i$  is the time period of the first donation, and a cohort  $e$  is a set of companies for which  $E_i = e$ ;  $Y_{i,e+l}^\infty$  is the counterfactual outcome if the donation was never made. Sun and Abraham (2021) further updated this specification with a weighted average<sup>3</sup>, where the weights correspond to the proportion of cohorts that undergo their initial treatment in period  $e$ , or at least  $l$  periods in relation to the treatment. These weights are normalized by the relative periods.

Table 1 and 2 present the Average Treatment Effect of the Treated (ATT) and standard errors for various model types and control groups with two outcome variables. Notably, models incorporating Sun and Abraham interactions, exhibit one of the smallest standard errors, implying the higher precision. Hence, the primary model in this paper relies on the interaction proposed by Sun and Abraham, given the nature of the data and the research objectives and limitation<sup>4</sup>.

The event study design can have two types of data structures: with a common or varying event date (Miller, 2023). In this research, a varying event date is employed, along with a grouping of treated, not yet treated, and never-treated companies. This means that the analysis includes companies that never made a donation and participated in public procurement, as well as those that made a donation and also participated in public procurement. The latter group exhibits variation in the year when the donation was made, and some of them made donations more than once.

To distinguish non-donating companies and establish the control group, we employed propensity score matching using the nearest neighbor algorithm on the entire population of

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<sup>3</sup>Likewise, Callaway and Sant'Anna (2021) address treatment effect heterogeneity by weighting averages based on the propensity score, with normalization to zero. The specification aims to reweight the covariates of both the treatment and control groups, ensuring a more balanced distribution.

<sup>4</sup>Callaway and Sant'Anna emphasize the staggered Difference-in-Differences framework, which, while potentially applicable to the research setup, does not adequately address the significant bias in interpreting coefficients arising from variations in the length of group exposure to the treatment

Table 1: Outcome - average income from public procurement contracts

	ATT	SE	Model	Control group	$Pr(> t )$
1	6769.684	1252.289	Two-way fixed effects	Never Treated	0.000
2	6884.510	1424.920	Sun and Abraham interactions	Never Treated	0.000
3	6447.551	2439.301	Imputation Method (two-stage DID)	Never Treated	0.001
4	5608.207	1492.747	Group-Time Average Treatment Effects	Never Treated	0.000
5	5089.229	1540.409	Group-Time Average Treatment Effects	Not Yet Treated	0.000

Table 2: Outcome - total value of public procurement contracts

	ATT	SE	Model	Control group	$Pr(> t )$
1	31595.96	5643.337	Two-way fixed effects	Never Treated	0.000
2	30040.70	4101.940	Sun and Abraham interactions	Never Treated	0.000
3	28849.25	7376.666	Imputation Method (two-stage DID)	Never Treated	0.003
4	25596.24	5044.270	Group-Time Average Treatment Effects	Never Treated	0.000
5	23894.89	5032.959	Group-Time Average Treatment Effects	Not Yet Treated	0.000

(a) Group-Time Average Treatment Effects models, as well as TWFE have a reference period set to -1, hence the difference in ATT from the rest of the models. The outcome variable is in 1000 RUB.

companies involved in Russian public procurement from 2011 to 2022. Following the methodology outlined in (Ham & Miratrix, 2022), the matching specifically focused on covariates. The matching process was conducted on a one-to-one basis, meaning that each donor company was paired with a non-donor possessing similar characteristics. The outcomes of the matching process by used covariates are detailed in Annex B. The distribution graphs indicate that the matching is particularly accurate for numerical variables such as income and the number of employees. However, it exhibits slightly lower precision for categorical covariates like region and sector, although it still ensures a reasonably balanced distribution across different localities and markets.

The model specifications align with standard event study specifications as outlined in Miller, 2023. The pre-event reference period is set as the year prior to the donation (denoted

as y-1)<sup>5</sup>. The control groups encompass companies that have never been treated but have participated in public procurement at any point, as well as companies that have participated in public procurement but have not yet made a donation. Given the relatively low overall number of observations, relying solely on not-yet-treated units could diminish statistical power and increase standard errors. Therefore, both specifications were tested. Considering the variation in the number of donations between 2011 and 2022, the results are presented within a time span of -5 to +7 years around the donation event.

The models incorporate controls for unit-specific trends to mitigate omitted variable bias and partially address endogeneity concerns. Each model includes fixed effects for both company and year, accounting for potential determinants at the company-year level that might influence the distribution of public procurement contracts. Additionally, clustered standard errors at the company level are integrated into the models, as well as robust standard errors controlling for heterogeneity. Given the research question's nature, we assume that a company experiences a single event—the first donation. Consequently, the model does not include the impact of multiple donations made by a company. Although we examine the effect of the first donation on different donor groups based on the number of times they have contributed, the analysis focuses exclusively on the relevance of the initial donation.

This study examines two outcome variables: the total value of public procurement contracts won by a company and the average value derived from public procurement, which is calculated by dividing the total sum of contract values by the total number of contracts won by a company in a given year. The final formula of this paper is

$$y_{it} = \text{Calender Year FEs} + \text{Company FEs} + \sum_{e \in \{0:7\}} \sum_{l=-5}^{-1} \delta_{e,l} (\mathbf{1}\{E_i = e\} \cdot D_{i,t}^l) + \epsilon_i^c,$$

with fixed effects representing company and calendar year time-invariant characteristics,  $\delta_{e,l}$  representing the weighted average for relative cohorts, the summations capturing the impact of the donation in lag and lead periods with reference period set to -1 and time prior and after donation limited to 5 years, and  $D_{i,t}^l$  being an indicator variable that equals 1 if company  $i$  is  $l$  periods away from the first donation at time  $t$ .

## 6 Data

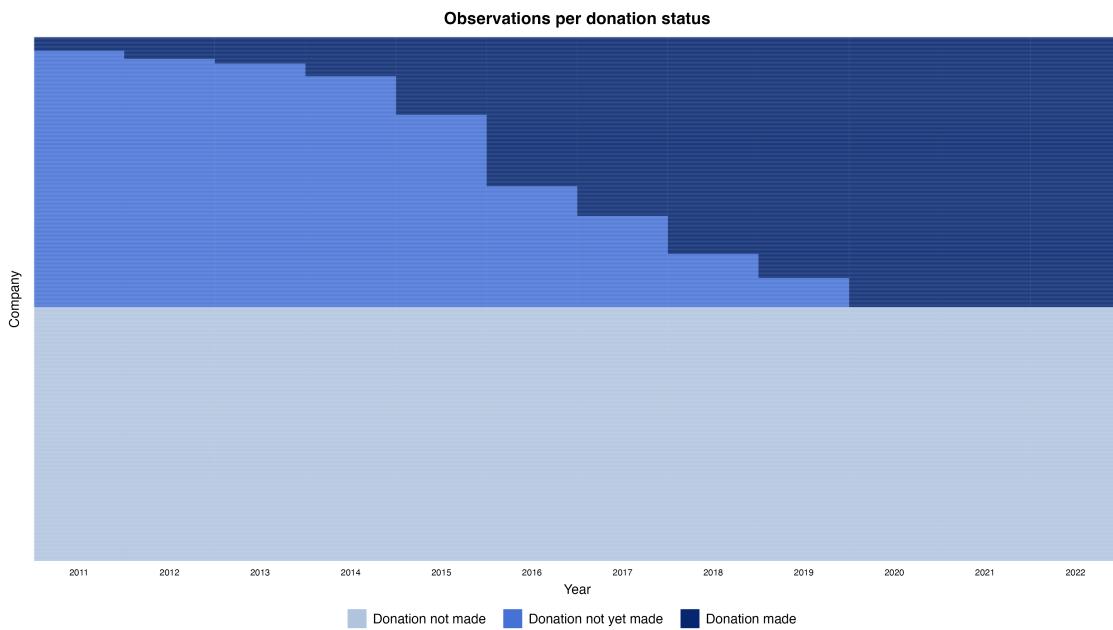
Several separate data sources were used to collect data for the analysis. To obtain data on United Russia's donors, the information provided by the NGO "Golos" within the framework of the "Party Wallet" project was used<sup>6</sup>. The information on donations has been manually collected by activists from the declarations of the parties that are available in the public

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<sup>5</sup>The 8th and 9th year after the donation, as well as 9th to 6th year prior the donation are included in the sample but with no dummy variable generated for them due to very low number of observations for these groups.

<sup>6</sup>At present, the government of the Russian Federation has declared NGO "Golos" a foreign agent and has a head of organization under prosecution for cooperation with undesirable organization. Therefore, some of the sources are experiencing disruptions in the operation online and do not provide "Party Wallet" data in open access.

**Figure 4:** Company's donation status over time



domain. The data span from 2005 to 2020 and provide information on funding for election campaigns and general party operations. For the purpose of the analysis, the total amount of donations per company in a particular year has been used. Number of unique donors in the dataset = 3400

Figure 4 illustrates the company matrix based on their donation status. Notably, exactly half of all observations did not make any donations, constituting the control group. The remaining companies exhibited a gradual increase in donations over time, with a spike in 2016 coinciding with the federal Duma elections. Post-2020, companies that had previously made donations show no variation in donation status, as a single donation was considered a permanent treatment for this research. To assess the impact on contract distribution, the data for the years 2021 and 2022 was retained, observing if donations in 2020 influenced contracts up to two years later.

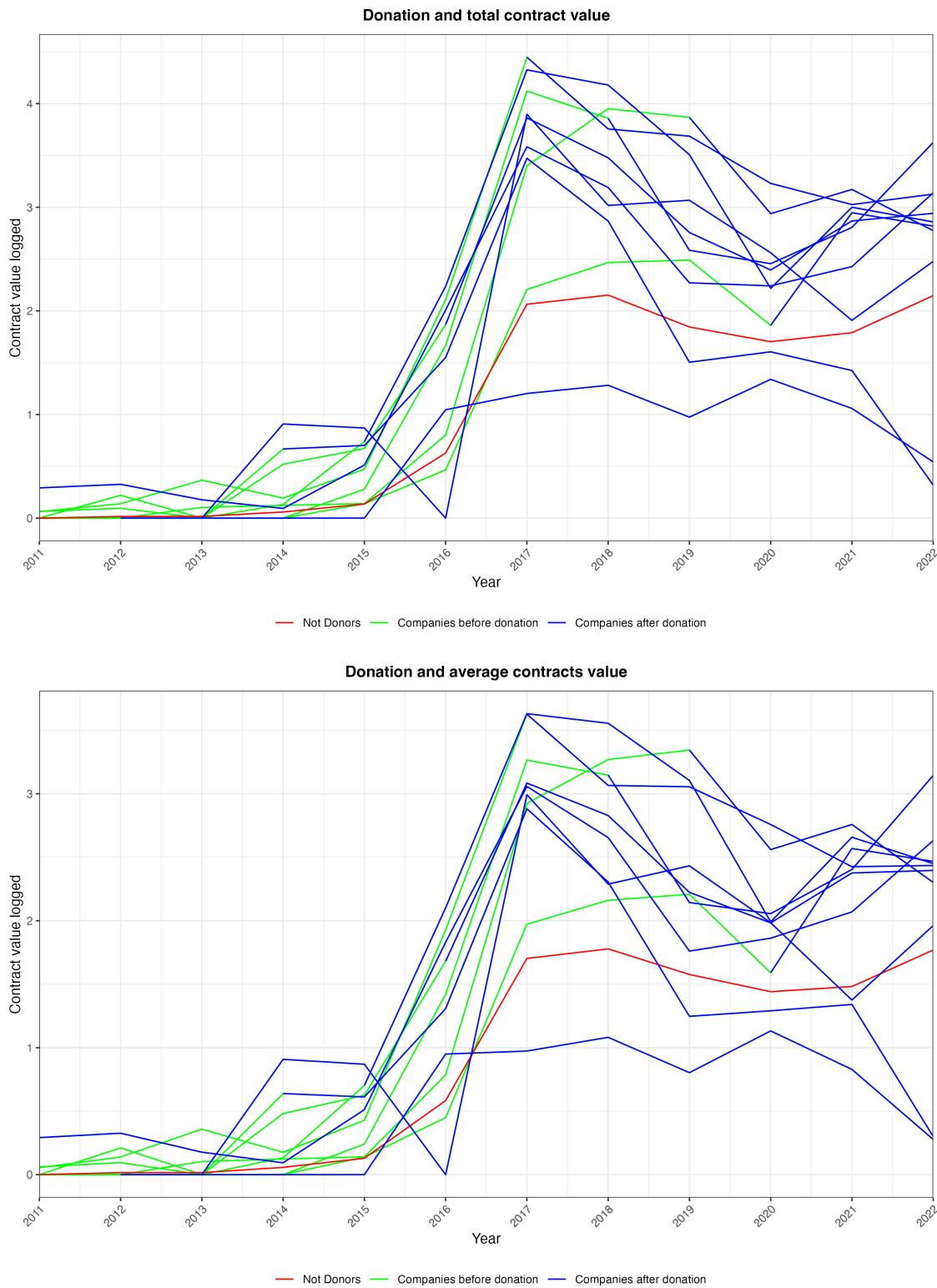
Next, company information was obtained from the Federal Tax Service (FNS) open data. The agency publishes information on all the companies and private enterprises that are registered in Russia (the total number of observations is approximately 6,000,000). The data gathered by FNS included tax identification, income, number of employees, address, and type of economic activity<sup>7</sup>.

The data on public procurement contracts was provided by the Government Transparency Institute<sup>8</sup>. The data contains contract-level information on public procurement regulated by

<sup>7</sup>For this purposes Russia uses standardized code of economic activity OKVED. The exact definition of markets per OKVED categories is presented in Annex A

<sup>8</sup>The data was provided by the Government Transparency Institute for research purposes. Technical

**Figure 5:** Contract value by type of company and cohort



Federal Law №44 (about two-thirds of all public contracts are covered by this law<sup>9</sup>). The data has been matched to the company data using the tax ID, and then matched to data on donors via tax identifier and year of contract or donation. The public procurement dataset contains about 10,000 records of companies that have ever donated, with about 1000 individual donation records (almost one third of all registered donors of United Russia party). The final dataset before matching included 1.5 million contracts for 700,000 companies for the period 2011 to 2021. After propensity score matching 1 to 1 (1 donor to 1 non-donor) and filtering to 2011-2022 time span, the final number of observations in the dataset is 20,370.

In line with the distribution overview depicted in Figure 4, Figure 5 provides an aggregated representation of the total and average contract values distributed by cohort. A cohort, in this context, is defined as a group of observations corresponding to companies that were treated (i.e., made donations) in the same year. The distribution pattern indicates a consistent trend, with the highest total and average values being prominent following the year of donation for nearly every cohort. Moreover, the distribution indicates that the average contract value shows marginal divergence from the total value. This implies that the observed contract values are not disproportionately influenced by exceptionally large contracts but rather reflect the typical value of contracts received by a company in a given year.

## 7 Results

Analytical model employed in this study assesses the influence of donations to the United Russia party on both the total and average values of public procurement contracts awarded to a company over an 11-year period relative to the year of the donation event. Since the timing of the donation event varies for each company, cohorts are formed based on the year of their initial donation. The model's findings reveal a statistically significant increase in both the total and average contract values following donations to the United Russia party. Figure 6 illustrates a 4-year pre-trend and the impact of the donation for up to 7 years post-event. Importantly, the model indicates no significant impact on outcome variables prior to the year of the donation event, affirming the non-violation of the main assumptions of the event study. Subsequently, both total and average contract values exhibit a substantial increase starting from the year of the donation, reaching a peak one year after the donation. This effect persists for 6 years post-donation with slight variations in coefficients and standard

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details can be found in: Fazekas, Mihály; Bence, Tóth; Abdou, Aly & Ahmed Al-Shaibani (2024) Global Contract-level Public Procurement Dataset. Data in Brief

<sup>9</sup>In Russia, public procurement procedures are governed by two primary laws: No. 223 and No. 44. The latter encompasses all public contracts granted by federal, regional, or municipal public agencies, while the former pertains specifically to public contracts awarded by companies with a 50% or higher state shareholding, as well as natural monopolies. While Law 223 allows organizations to establish their own requirements for public procurement, Federal Law 44 clearly delineates the responsibilities of both contracting parties. This research focuses on contracts regulated by Federal Law №44 due to a) a number of observations since this law covers vast majority of all contracts in the country b) anticipation that donations show effect on procurement contracts which are distributed by public institutions rather than state-owned enterprises c) expectation that donation serve as a form of interference with competition, which is also higher under 44 Federal Law making this instrument more relevant

errors.

Annex C provides precise estimates for each relative time period, along with standard errors clustered at the company level and heteroskedasticity-robust standard errors. Specifically, the year of donation and the year after the donation contribute to an increase in total contract value by 17 and 43 million rubles, respectively. Similarly, average contract value experiences a rise of 6 and 8,5 million rubles in the respective years. Importantly, the cumulative effect of donations influences roughly 70% of the total value of contracts secured by donor companies<sup>10</sup>.

Although the model incorporates potential time-invariant company characteristics, it is essential to investigate whether the observed effect remains consistent across diverse groups of companies. An initial and apparent criterion for differentiation is based on sectoral distinctions. We anticipate observing an increase in contract value within markets that are of particular interest to the dominant party or can be used for its needs. Figure 6 illustrates the model's outcomes for two markets that exhibit a significant effect: Construction Work, and Wholesales and Retail Trade. These specific markets were chosen due to the absence of a noteworthy pre-trend, indicating compliance with event study assumptions, and a substantial increase in average contract value following the donation event (for exact coefficients and full list of sectors see Annex D).

The findings highlight the construction and sales sectors as the most prominent and consistently impacted markets, primarily due to the sheer volume of observations and the overall share of donations. However, the construction sector stands out as more coherent and stable in the increase in the total value of contracts, with the effect being visible immediately after the donation was made. Simultaneously, noticeable rises in total contract values are observed in the Wholesale and Retail sector, demonstrating an overall upward trend, albeit with insignificant coefficients two years after the year of donation. The act of donation elevates the total contract value by 10 million RUB in Wholesale and Retail and 66 million RUB in construction. This translates to 61% and 70% of the total contract value among donors, respectively.

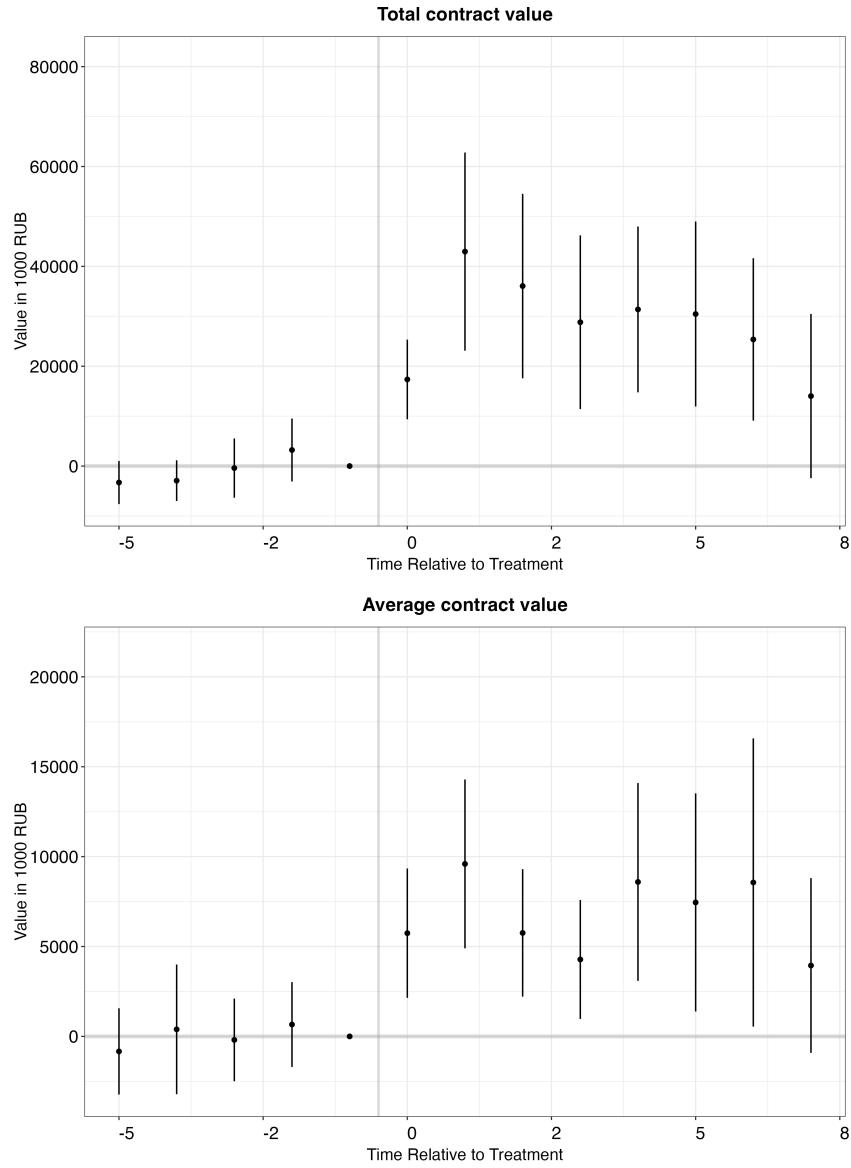
Another factor that may influence the event's outcome is the number of donations a company has made to United Russia over time. The sample was divided into four groups based on the number of donations made by a company, ranging from 1 to 4 (the maximum number of donations is 5, but only four companies reached that level, so they were included in the last group). Figure 8 illustrates the results (with exact coefficients provided in Annex E), revealing a distinct variation in the impact of donations across different groups.

The results indicate that the first donation has the most substantial effect compared to subsequent donations, with a consistent decline in impact with each additional donation made. For companies making a single donation, the effect on average contract value is 20%. However, for companies making two donations, the effect decreases to 4% and is statistically insignificant.

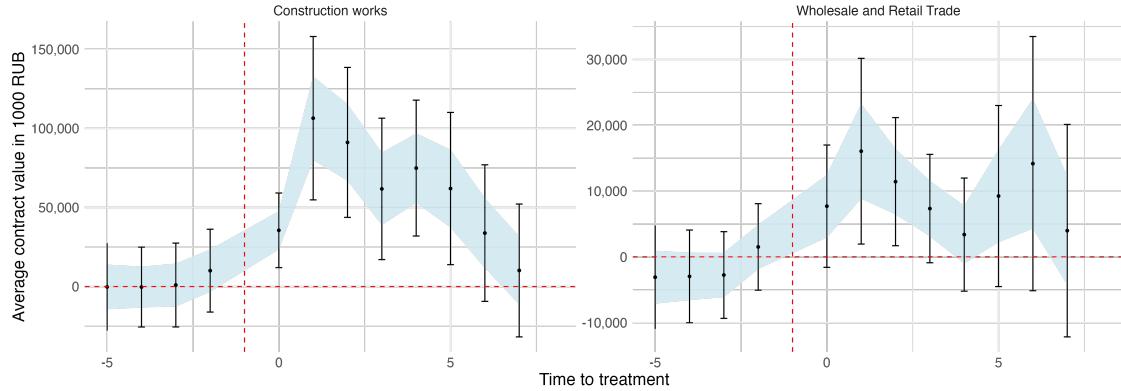
The final source of heterogeneity in effects is companies' earnings, which serve as a proxy for company size. Companies of different sizes may benefit differently from donations to the dominant party. To explore this, the sample was divided into four quantiles based on the

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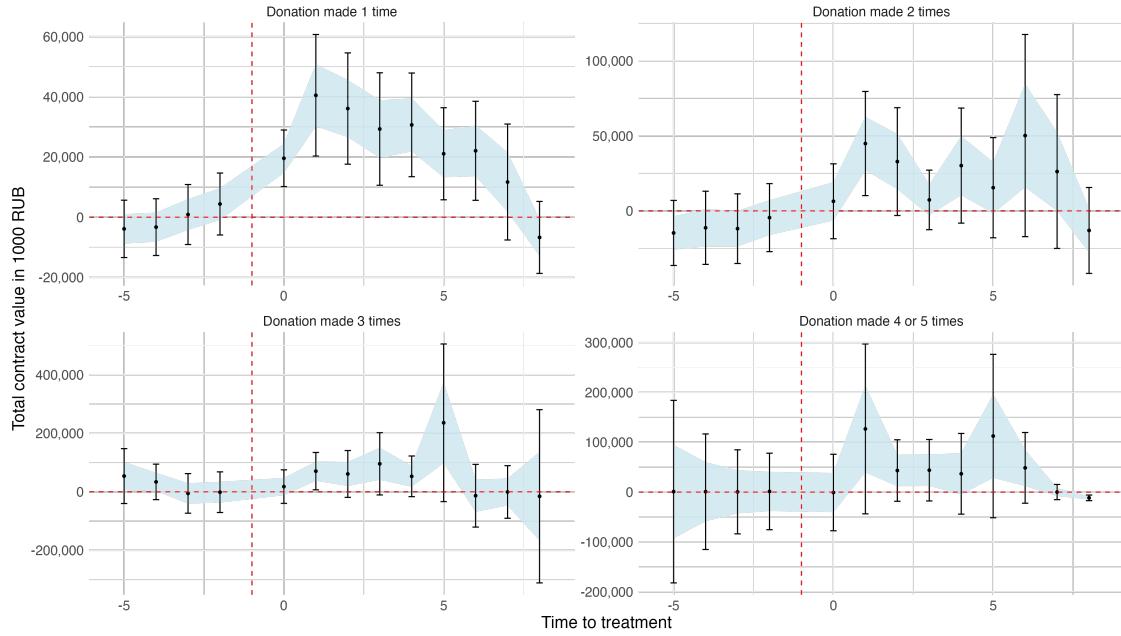
<sup>10</sup>The share is calculated as ATT / Average value of contracts in treated group \* 100, in this case 30040/40852\*100

**Figure 6:** Event study model

(a) The model used is Sun & Abraham interaction. The period marked as -1 serves as a reference. Time intervals -9 to -6 and 8 to 10 are encompassed in the sample; however, no dummy variables were generated for these periods due to a limited number of observations. The reference cohort consists of companies that have never made donations.

**Figure 7:** Event study model: sampling for sectors

(a) The model used is Sun & Abraham interaction. The period marked as -1 serves as a reference. Time intervals -9 to -6 and 8 to 10 are encompassed in the sample; however, no dummy variables were generated for these periods due to a limited number of observations. The reference cohort consists of companies that have never made donations. Each sector was sampled from a full list of donors and matched non-donors, with the models performed separately on each sample. The presented sectors exhibit no parallel trends violations and demonstrate significant coefficients.

**Figure 8:** Event study model: sampling for different number of donations

(a) The model used is Sun & Abraham interaction. The period marked as -1 serves as a reference. Time intervals -9 to -6 and 8 to 10 are encompassed in the sample; however, no dummy variables were generated for these periods due to a limited number of observations. The reference cohort consists of companies that have never made donations. Each sample was extracted from a full list of donors and matched non-donors depending on the number of donations made by a company.

total earnings of each company in the dataset. Figure 9 illustrates the model results for each of the four groups (refer to coefficients in Annex F).

The model indicates that donations have a long-lasting and significant effect primarily in the third and fourth quantiles of companies' earnings, with the wealthiest companies experiencing the most substantial return in the form of public procurement contracts. The first quantile also shows a statistically significant increase for three years after the donation, although the average effect is lower. The increase due to donation for companies in the fourth quantile accounts for 75% of the average contract value, and for companies in the third quantile, it constitutes 70%.

Therefore, the overall heterogeneous effect yields the following insights: United Russia donors with high earnings, who make a single donation experience a significant increase in the values of contracts they win through public procurement. Moreover, such increase can be observed in three sectors, with Construction Sector demonstrating the most robust jump in public procurement returns.

## 8 Case studies

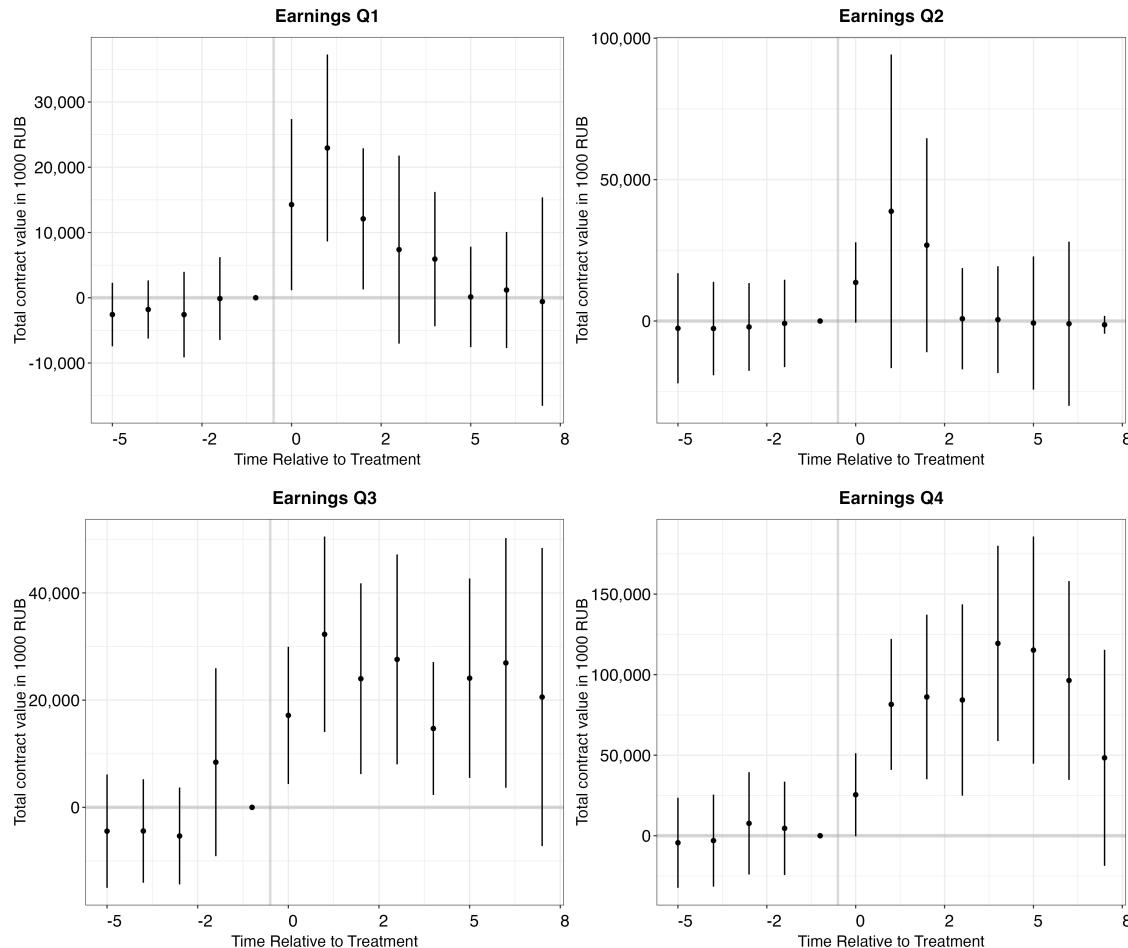
Among the companies in the construction sector, LLC Transsignalstroy stands out as the largest donor to United Russia. While not the biggest player in the sector, it ranks among the top 40 construction companies in Russia, boasting an annual turnover of 1.6 billion rubles in 2022. Established in 2001, the company made contributions to United Russia in 2016 and 2019, amounting to 15,000,000 and 43,300,000 RUB, respectively. Notably, prior to 2016, Transsignalstroy exhibited relatively stable revenues, hovering around 1.5 million RUB. A year before its first donation, in 2015, there was a significant increase, with revenues reaching 8.5 million rubles and an annual turnover of 1.5 billion RUB. In 2016, the company experienced a sharp spike, reaching 389 million RUB in revenue and an annual turnover of 3.4 billion RUB. This spike coincided with the company securing numerous contracts, primarily from Russian Railways (JSCo RZD). Interestingly, only the impact of the first donation is reflected in Transsignalstroy's revenues; after the second one in 2019, they reverted to a decline. In total, the company secured approximately 750 public procurement contracts, with 660 contracts awarded during the years 2016 and 2017, and only 24 contracts obtained in the period preceding these years.

An illustration of a considerably less notable company in terms of market significance is LLC "Agni Elevators RUS." This firm is engaged in the wholesale trade of lifting and transport machinery and equipment. Established in 2018, it made its inaugural and sole donation to United Russia in 2020. Prior to this, the company had not secured any contracts in public procurement, and in the year 2020, its revenue amounted to 159 million RUB. Subsequently, the company began winning contracts, primarily from the "Capital Repair Fund of Pskov Oblast," a state fund responsible for the reconstruction of old buildings.

## 9 Discussion and Conclusion

The presented results illustrate that the dynamics of relationships between donors and the ruling party in an authoritarian regime somewhat mirror the rationale behind donations in

**Figure 9:** Event study model: sampling for income groups



(a) The model used is Sun & Abraham interaction. The period marked as -1 serves as a reference. Time intervals -9 to -6 and 8 to 10 are encompassed in the sample; however, no dummy variables were generated for these periods due to a limited number of observations. The reference cohort consists of companies that have never made donations. Each sample was extracted from a full list of donors and matched non-donors depending on the income quartiles (0-25%, 26-50%, 51-75%, 75%-100%).

democracies, distinguishing between ideological and opportunistic donors. However, there are a few distinctive differences related to the logic of political survival in dictatorships and the nature of business-state relationships. In a democratic setting, providing donations in exchange for benefits is more likely to result in gaining access to the decision-making process or influencing legislative behavior favorably towards the company (Acton & Hawkins, 2022; Powell, 2012). In contrast, in authoritarian conditions, such exchanges lead to direct monetary benefits for both parties—funds for electoral campaigns and party operations are traded for money obtained through public procurement contracts. Hence while in a democratic system, corporate donations may aim to influence procedural barriers, in an autocracy, they serve to gain access to the distribution of public funds.

Second, the selection of sectors where this dynamic persists suggests that such exchanges are not common to all business entities but rather prevalent among those operating in the construction sector and retail trade. Two possible reasons may account for this. First, these sectors could exhibit lower transparency, making them more susceptible to corruption. For instance, the construction sector is known for its susceptibility to corruption due to the scale of projects, their non-comparability, lack of standardization, extensive subcontracting, and other related factors. Additionally, sectors such as construction and wholesale might also be strategically utilized by the government. For example, a government aims to construct a large stadium in the city center. Such a prominent infrastructure project would capture the attention of voters and carry symbolic significance for the politician spearheading the initiative. The crucial decision then arises: to whom should the construction be delegated? Given the significant opportunity to build and generate economic profits, the project is often awarded to a company with ties to the state. The extent of these connections varies based on the project's scale. Making a donation to the dominant party could be a way of establishing such connection<sup>11</sup>. The findings also indicate that the impact of an increase in public procurement value is observable in the short term for small-income companies and enduring in the long term for larger enterprises. This implies that, for small companies, making a donation may serve as an entry point into the market for public procurement contracts, almost constituting a direct exchange of funds. Conversely, for large companies, a donation signals an established connection between the dominant party and the company, indicating involvement in institutionalized grand corruption.

In summary, the findings indicate a departure from the expectation that United Russia enjoys broad support and ideological popularity. Instead, support for the dominant party appears to be driven by opportunistic and strategic considerations. Corporate donations frequently aim to secure private benefits rather than endorsing the party's policies. While this system is inherently corrupt, it also implies that the support for the dominant party hinges on the specific advantages it offers rather than ideological alignment. This assumes that the system is less stable than one might anticipate and can only be sustained as long as there are sufficient resources available to exchange for support. Following the logic proposed by De

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<sup>11</sup>To illustrate, the infamous "Gazprom Stadium" in Saint Petersburg, known for being one of the largest corruption projects in terms of embezzled funds, was constructed under the supervision of a former vice-governor of the city, who was later imprisoned for orchestrating a grand corruption scheme during the stadium's construction. The project also involved the participation of companies connected to Russian billionaires such as Oleg Deripaska and Gennadiy Timchenko (Alexander Ermakov, 2021; Lyubov Chizhova, 2018).

Mesquita et al., 2005, the political survival of autocrats is contingent on the resources they can distribute to their winning coalition and core group of supporters. This perspective also holds relevance for modern Russia, where the phenomenon of popular support for the political regime is actively studied (Kuzio, 2023; Rosenfeld, 2023). Considering the historical context and the roots of support established prior to the onset of the full-scale Russian invasion of Ukraine, it is reasonable to assume that, at present, this support is as well largely contingent on existing resources and the manner in which they are distributed among supporters.

## References

- Acton, C., & Hawkins, B. (2022). Are UK alcohol industry political donations intended to influence public health policies?—Analysis of publicly available data on donations and lobbying. *Journal of Public Affairs*, 22, e2740.
- Alexander Ermakov. (2021, November). Criminal Guidelines for "Zenit Arena": Why Entrepreneurs Operating at the Stadium Are Under Investigation.
- Arias, E., Hollyer, J. R., & Rosendorff, B. P. (2018). Cooperative autocracies: Leader survival, creditworthiness, and bilateral investment treaties. *American Journal of Political Science*, 62(4), 905–921.
- Bak, D., & Moon, C. (2016). Foreign direct investment and authoritarian stability. *Comparative Political Studies*, 49(14), 1998–2037.
- Barber, M. (2016). Donation motivations: Testing theories of access and ideology. *Political Research Quarterly*, 69(1), 148–159.
- Barr, B., Dalton, G., Nice, A., & Tingay, P. (2020, February). Rules for funding for political parties: The main source of public funding for political parties is 'Short money'.
- Basualdo, V. (2021). Business and the military in the argentine dictatorship (1976–1983): Institutional, economic, and repressive relations. *Big Business and Dictatorships in Latin America: A Transnational History of Profits and Repression*, 35–62.
- Basualdo, V., Berghoff, H., & Bucheli, M. (2020). *Big Business and dictatorships in Latin America: A transnational history of profits and repression*. Springer Nature.
- Basualdo, V., Berghoff, H., & Bucheli, M. (2021). Crime and (no) punishment: Business corporations and dictatorships. *Big business and dictatorships in Latin America: A transnational history of profits and repression*, 1–33.
- Bechetti, L., Ciciretti, R., & Hasan, I. (2009). Corporate social responsibility and shareholder's value: An event study analysis.
- Birch, S. (2022). Private electoral finance and democratic theory. *Constellations (Oxford, England)*, 29(4), 401–517.
- Bogliaccini, J. A., Geymonat, J., & Operetti, M. (2021). Big business and bureaucratic authoritarianism in uruguay: A network-based story of policy infiltration for self-preservation. *Big Business and Dictatorships in Latin America: A Transnational History of Profits and Repression*, 127–156.
- Boix, C., & Svolik, M. W. (2013). The foundations of limited authoritarian government: Institutions, commitment, and power-sharing in dictatorships. *The Journal of Politics*, 75(2), 300–316.
- Borusyak, K., Jaravel, X., & Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. *arXiv preprint arXiv:2108.12419*.
- Brown, A. R. (2013). Does money buy votes? the case of self-financed gubernatorial candidates, 1998–2008. *Political Behavior*, 35, 21–41.
- Butts, K., & Gardner, J. (2021). {Did2s}: Two-stage difference-in-differences. *arXiv preprint arXiv:2109.05913*.
- De Mesquita, B. B., Smith, A., Siverson, R. M., & Morrow, J. D. (2005). *The logic of political survival*. MIT press.
- Diaz-Cayeros, A., Estévez, F., & Magaloni, B. (2016). *The political logic of poverty relief: Electoral strategies and social policy in Mexico*. Cambridge University Press.

- Dorsch, M. T., & Maarek, P. (2018). Rent extraction, revolutionary threat, and coups in non-democracies. *Journal of Comparative Economics*, 46(4), 1082–1103.
- Dosal, P. J. (1993). *Doing business with the dictators: A political history of United Fruit in Guatemala, 1899-1944*. Rowman & Littlefield Publishers.
- El Tarouty, S. (2016). *Businessmen, clientelism, and authoritarianism in Egypt*. Springer.
- Esen, B., & Gumuscu, S. (2018). Building a competitive authoritarian regime: State–business relations in the AKP’s Turkey. *Journal of Balkan and Near Eastern Studies*, 20(4), 349–372.
- Fazekas, M., Lukács, P. A., & Tóth, I. J. (2015). The political economy of grand corruption in public procurement in the construction sector of Hungary. *Government Favouritism in Europe the anticorruption report*, 3, 53–68.
- Federal Election Committee. (n.d.). Introduction to campaign finance and elections.
- Fisher, J. (1994). Why do companies make donations to political parties? *Political Studies*, 42(4), 690–699.
- Frye, T., Reuter, O. J., & Szakonyi, D. (2014). Political machines at work voter mobilization and electoral subversion in the workplace. *World politics*, 66(2), 195–228.
- Garnett, H. A., Pruyers, S., Young, L., & Cross, W. P. (2022). Lifeblood of the party: Motivations for political donations in canada. *American Review of Canadian Studies*, 52(4), 422–445.
- Geddes, B., Wright, J., & Frantz, E. (2014). Autocratic breakdown and regime transitions: A new data set. *Perspectives on politics*, 12(2), 313–331.
- Geddes, B., & Zaller, J. (1989). Sources of popular support for authoritarian regimes. *American Journal of Political Science*, 319–347.
- Gehlbach, S., & Keefer, P. (2012). Private investment and the institutionalization of collective action in autocracies: Ruling parties and legislatures. *The Journal of Politics*, 74(2), 621–635.
- Gerring, J., & Thacker, S. C. (2004). Political institutions and corruption: The role of unitarism and parliamentarism. *British Journal of Political Science*, 34(2), 295–330.
- Gomez, E. T., & Jomo, K. S. (1999). *Malaysia’s political economy: Politics, patronage and profits*. CUP Archive.
- Gonzalo, F. M. (2013). Forced labor, public policies, and business strategies during Franco’s dictatorship: An interim report. *Enterprise & Society*, 14(1), 182–213.
- Greene, K. F. (2010). The political economy of authoritarian single-party dominance. *Comparative political studies*, 43(7), 807–834.
- Guriev, S., & Treisman, D. (2020). The popularity of authoritarian leaders: A cross-national investigation. *World Politics*, 72(4), 601–638.
- Hadiz, V., & Robison, R. (2004). *Reorganising power in Indonesia: The politics of oligarchy in an age of markets*. Routledge.
- Ham, D. W., & Miratrix, L. (2022). Benefits and costs of matching prior to a difference in differences analysis when parallel trends does not hold. *arXiv preprint arXiv:2205.08644*.
- Hollyer, J. R., & Wantchekon, L. (2015). Corruption and ideology in autocracies. *JL Econ. & Org.*, 31, 499.
- Huang, D., & Chen, M. (2020). Business lobbying within the party-state: Embedding lobbying and political co-optation in China. *The China Journal*, 83(1), 105–128.

- Huneeus, C., & Undurraga, T. (2021). Authoritarian rule and economic groups in Chile: A case of winner-takes-all politics. *Big Business and Dictatorships in Latin America: A Transnational History of Profits and Repression*, 91–125.
- Jensen, N., & Wantchekon, L. (2004). Resource wealth and political regimes in Africa. *Comparative political studies*, 37(7), 816–841.
- Kalinin, K. (2016). The social desirability bias in autocrat's electoral ratings: Evidence from the 2012 Russian presidential elections. *Journal of elections, public opinion and parties*, 26(2), 191–211.
- Kim, W., & Gandhi, J. (2010). Coopting workers under dictatorship. *The Journal of Politics*, 72(3), 646–658.
- Kunicova, J., & Rose-Ackerman, S. (2005). Electoral rules and constitutional structures as constraints on corruption. *British journal of political science*, 35(4), 573–606.
- Kuzio, T. (2023). Imperial nationalism as the driver behind Russia's invasion of Ukraine. *Nations and Nationalism*, 29(1), 30–38.
- Lyubov Chizhova. (2018). This Will Affect Russia's Image": Corruption and the FIFA World Cup.
- Mani, A., & Mukand, S. (2007). Democracy, visibility and public good provision. *Journal of Development Economics*, 83(2), 506–529. <https://doi.org/10.1016/j.jdeveco.2005.06.008>
- Mauk, M. (2017). Regime support and its sources in democracies and autocracies. *Conference Paper and Talk, the Political Sociology of Trust*.
- Mauk, M. (2020). *Citizen support for democratic and autocratic regimes*. Oxford University Press, USA.
- Miller, D. L. (2023). An introductory guide to event study models. *Journal of Economic Perspectives*, 37(2), 203–230.
- Molitor, D. (2018). The evolution of physician practice styles: Evidence from cardiologist migration. *American Economic Journal: Economic Policy*, 10(1), 326–356.
- Mudhoffir, A. M., & A'yun, R. Q. (2021). Doing business under the framework of disorder: Illiberal legalism in Indonesia. *Third World Quarterly*, 42(11), 2651–2668.
- Nicosia, F. R., & Huener, J. (2004). *Business and industry in nazi germany* (Vol. 2). Berghahn Books.
- Noelle-Neumann, E., & Petersen, T. (2004). The spiral of silence and the social nature of man. *Handbook of political communication research*, 339–356.
- Pedreira Campos, P. H. (2021). Building the dictatorship: Construction companies and industrialization in Brazil. *Big Business and Dictatorships in Latin America: A Transnational History of Profits and Repression*, 63–89.
- Powell, L. W. (2012). *The influence of campaign contributions in state legislatures: The effects of institutions and politics*. University of Michigan Press.
- Powell, L. W., Wilcox, C., Francia, P. L., Herrnson, P. S., & Green, J. C. (2003). *The financiers of congressional elections: Investors, ideologues, and intimates*. Columbia University Press.
- Reuter, O. J., & Remington, T. F. (2009). Dominant party regimes and the commitment problem: The case of United Russia. *Comparative political studies*, 42(4), 501–526.
- Rose-Ackerman, S. (1996). Democracy and 'grand'corruption. *International social science journal*, 48(149), 365–380.

- Rosenfeld, B. (2023). Survey research in Russia: In the shadow of war. *Post-Soviet Affairs*, 39(1-2), 38–48.
- Sakwa, R. (2014). *Putin and the oligarch: The khodorkovsky-yukos affair*. Bloomsbury Publishing.
- Sallai, D., & Schnyder, G. (2021). What is “authoritarian” about authoritarian capitalism? The dual erosion of the private–public divide in state-dominated business systems. *Business & Society*, 60(6), 1312–1348.
- Schedler, A. (2006). *Electoral authoritarianism: The dynamics of unfree competition*. Lynne Rienner Publishers.
- Silva, E. (2019). *The state and capital in Chile: Business elites, technocrats, and market economics*. Routledge.
- Singer, M. (2009). Buying voters with dirty money: The relationship between clientelism and corruption. *APSA 2009 Toronto Meeting Paper*.
- Sirotkina, E., & Zavadskaya, M. (2020). When the party’s over: Political blame attribution under an electoral authoritarian regime. *Post-soviet affairs*, 36(1), 37–60.
- Sixsmith, M. (2010). *Putin’s oil: The Yukos affair and the struggle for Russia*. Bloomsbury Publishing USA.
- Stillerman, J. (2003). Space, strategies, and alliances in mobilization: The 1960 metalworkers’ and coal miners’ strikes in Chile. *Mobilization: An International Quarterly*, 8(1), 65–85.
- Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2), 175–199.
- Titl, V., & Geys, B. (2019). Political donations and the allocation of public procurement contracts. *European Economic Review*, 111, 443–458.
- van der Ploeg, F. (2011). Natural resources: Curse or blessing? *Journal of Economic literature*, 49(2), 366–420.
- Wang, Q.-J., Feng, G.-F., Wang, H.-J., & Chang, C.-P. (2021). The impacts of democracy on innovation: Revisited evidence. *Technovation*, 108, 102333.
- Wintrobe, R. (2000). *The political economy of dictatorship*. Cambridge University Press.
- Yadav, V., & Mukherjee, B. (2016). *The politics of corruption in dictatorships*. Cambridge University Press.

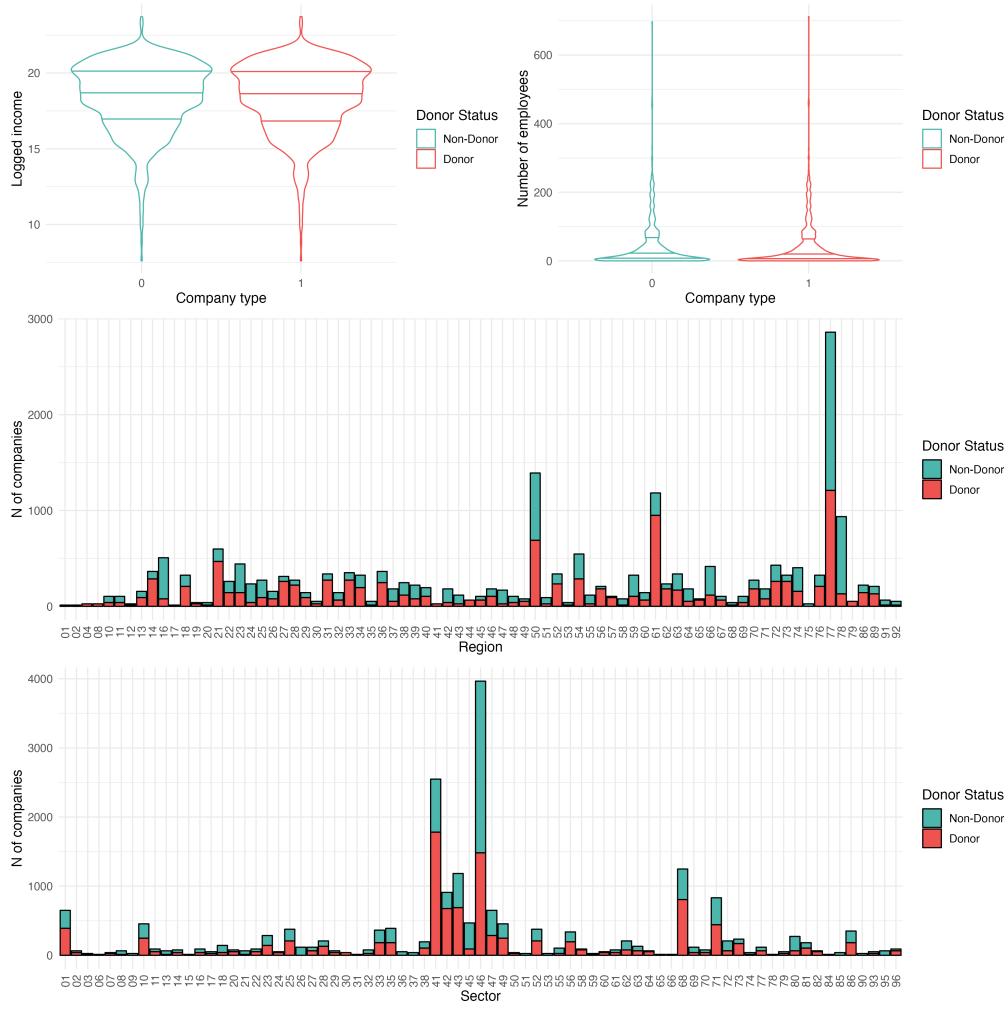
## A Sector categories

Table 3: OKVED Categories

OKVED 2 digits	Corresponding Sector
01, 02, 03	Agriculture, Forestry, Hunting, Fishing
05, 06, 07, 09	Mining and Extraction of Mineral Resources
10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33	Manufacturing and Processing Industries
35, 36, 37, 38, 39	Energy and Water Supply
41, 42, 43, 68, 77, 81	Construction works
45, 46, 47	Wholesale and Retail Trade
49, 50, 51, 52, 53	Transportation
58, 59, 60, 61, 62, 63	Information and Communication Activities
78, 79, 81, 82	Administrative and Business Support Services
84, 80	Military and Security Activities
55, 56, 85, 86, 87, 88	Healthcare and Social Services Activities
90, 93, 95, 96	Cultural, Sports, Leisure Services Sector
64, 65, 66	Financial and Insurance Services

## B Distribution of covariates by matched groups

**Figure 10:** Matching results by covariates



## C Coefficients for general model

Results for Contract Value

Relative event time	Estimate	SE	t value	$Pr(> t )$	SE Robust
Event year -5	-3293.299	2203.228	-1.495	0.135	4649.713
Event year -4	-2923.965	2081.978	-1.404	0.160	4504.636
Event year -3	-405.793	3027.529	-0.134	0.893	4709.338
Event year -2	3216.275	3219.680	0.999	0.318	4815.144
Event year	17348.384	4070.305	4.262	0.000	4464.250
Event year +1	42955.587	10122.341	4.244	0.000	9076.768
Event year +2	36056.124	9425.829	3.825	0.000	8364.961
Event year +3	28807.948	8872.257	3.247	0.001	8277.750
Event year +4	31377.901	8473.991	3.703	0.000	7832.214
Event year +5	30453.596	9450.285	3.223	0.001	9093.346
Event year +6	25364.120	8296.761	3.057	0.002	8502.388
Event year +7	14014.944	8390.127	1.670	0.095	8866.457

(a) OLS estimation, Dep. Var.: Sum44; Observations: 18,791; Fixed-effects: INN: 1,566, Year: 12  
RMSE: 102,298.0; Adj. R2: 0.21913; Within R2: 0.016346

Results for average contract value

Relative event time	Estimate	SE	t value	$Pr(> t )$	SE Robust
Event year -5	-835.777	1481.201	-0.564	0.573	4649.713
Event year -4	391.795	1927.565	0.203	0.839	4504.636
Event year -3	-195.290	1496.062	-0.131	0.896	4709.338
Event year -4	661.645	1558.784	0.424	0.671	4815.144
Event year	5741.596	1870.819	3.069	0.002	4464.250
Event year +1	9594.485	2363.425	4.060	0.000	9076.768
Event year +2	5757.052	1781.935	3.231	0.001	8364.961
Event year +3	4279.939	1779.117	2.406	0.016	8277.750
Event year +4	8591.131	2683.993	3.201	0.001	7832.214
Event year +5	7452.347	2778.031	2.683	0.007	9093.346
Event year +6	8560.737	3829.471	2.235	0.025	8502.388
Event year +7	3943.516	3137.323	1.257	0.209	8866.457

(a) OLS estimation, Dep. Var.: avinc; Observations: 18,791; Fixed-effects: INN: 1,566, Year: 12  
RMSE: 31,650.2; Adj. R2: 0.171804; Within R2: 0.010033

## D Coefficients for sectoral model

Time to treatment	Estimate	SE Robust	t value	p value	model
-5	-3786.746	6043.008	-0.627	0.533	administration
-4	-2311.111	6050.093	-0.382	0.704	administration
-3	-2319.030	6051.934	-0.383	0.703	administration
-2	-2974.027	6178.658	-0.481	0.632	administration
0	-1281.335	8431.776	-0.152	0.880	administration
1	13292.847	6327.485	2.101	0.040	administration
2	16153.686	12326.832	1.310	0.195	administration
3	55692.025	43523.489	1.280	0.205	administration
4	-499.307	8971.896	-0.056	0.956	administration
5	-275.240	13694.110	-0.020	0.984	administration
6	-276.309	13694.841	-0.020	0.984	administration
7	-1070.224	13732.003	-0.078	0.938	administration

Observations: 120; RMSE: 16,606.1; Adj. R<sup>2</sup>: 0.213733; Within R<sup>2</sup>: 0.448313

-5	-203.596	14102.786	-0.014	0.988	construction
-4	-289.542	12877.247	-0.022	0.982	construction
-3	990.186	13519.154	0.073	0.942	construction
-2	10079.773	13353.229	0.755	0.450	construction
0	35561.779	12030.967	2.956	0.003	construction
1	106426.105	26336.292	4.041	0.000	construction
2	91133.093	24175.039	3.770	0.000	construction
3	61743.006	22801.117	2.708	0.007	construction
4	74894.296	21906.963	3.419	0.001	construction
5	61969.706	24547.338	2.524	0.012	construction
6	33821.516	22018.445	1.536	0.125	construction
7	10192.591	21418.001	0.476	0.634	construction

Observations: 4,619; RMSE: 190,606.0; Adj. R<sup>2</sup>: 0.225903; Within R<sup>2</sup>: 0.045672

-5	-3091.425	4008.842	-0.771	0.441	sales
-4	-2962.132	3593.402	-0.824	0.410	sales
-3	-2756.596	3361.714	-0.820	0.412	sales
-2	1513.742	3352.850	0.451	0.652	sales
0	7706.307	4741.918	1.625	0.104	sales
1	16059.459	7200.773	2.230	0.026	sales
2	11431.531	4967.306	2.301	0.021	sales
3	7343.030	4202.696	1.747	0.081	sales
4	3385.144	4384.227	0.772	0.440	sales
5	9245.657	7019.322	1.317	0.188	sales
6	14173.260	9855.303	1.438	0.150	sales
7	3984.813	8236.684	0.484	0.629	sales

Time to treatment	Estimate	SE Robust	t value	p value	model
Observations: 5,543; RMSE: 29,717.7; Adj. R <sup>2</sup> : 0.29068; Within R <sup>2</sup> : 0.05008					
-5	658.386	10932.833	0.060	0.952	social
-4	-1115.742	9713.915	-0.115	0.909	social
-3	-3442.051	8137.487	-0.423	0.672	social
-2	-5045.316	8476.676	-0.595	0.552	social
0	13782.823	22077.780	0.624	0.533	social
1	156.496	9790.988	0.016	0.987	social
2	13683.364	19445.459	0.704	0.482	social
3	-11350.491	9062.454	-1.252	0.211	social
4	5962.165	19918.575	0.299	0.765	social
5	366.277	10724.918	0.034	0.973	social
6	-20093.254	9159.518	-2.194	0.029	social
7	-13169.568	7658.981	-1.719	0.086	social
Observations: 766; RMSE: 64,993.0; Adj. R <sup>2</sup> : 0.376182; Within R <sup>2</sup> : 0.157273					
-5	-2662.704	3087.187	-0.863	0.388	industry
-4	-2400.099	2687.437	-0.893	0.372	industry
-3	2482.666	4956.503	0.501	0.616	industry
-2	-1618.312	2643.610	-0.612	0.540	industry
0	4791.126	4694.586	1.021	0.308	industry
1	2257.066	5739.178	0.393	0.694	industry
2	-2361.600	3437.853	-0.687	0.492	industry
3	-1843.105	3686.390	-0.500	0.617	industry
4	6259.916	8737.046	0.716	0.474	industry
5	-4483.241	1666.563	-2.690	0.007	industry
6	-4174.996	2010.636	-2.076	0.038	industry
7	-3999.547	1547.927	-2.584	0.010	industry
Observations: 2,711; RMSE: 29,173.1; Adj. R <sup>2</sup> : 0.17378; Within R <sup>2</sup> : 0.041326					
-5	-3.940	29.122	-0.135	0.892	agriculture
-4	-4.265	24.746	-0.172	0.863	agriculture
-3	28.944	44.790	0.646	0.518	agriculture
-2	-3.403	35.960	-0.095	0.925	agriculture
0	47.928	59.120	0.811	0.418	agriculture
1	75.769	76.510	0.990	0.322	agriculture
2	6.065	56.258	0.108	0.914	agriculture
3	73.961	80.781	0.916	0.360	agriculture
4	263.460	119.503	2.205	0.028	agriculture
5	896.568	551.052	1.627	0.104	agriculture
6	349.258	193.181	1.808	0.071	agriculture
7	227.978	198.880	1.146	0.252	agriculture

Time to treatment	Estimate	SE Robust	t value	p value	model
Observations: 684; RMSE: 546.9; Adj. R <sup>2</sup> : 0.432478; Within R <sup>2</sup> : 0.482046					
-5	0.000	42.362	0.000	1.000	mining
-4	32.967	36.091	0.913	0.366	mining
-3	0.000	42.362	0.000	1.000	mining
-2	0.000	42.362	0.000	1.000	mining
0	0.000	42.362	0.000	1.000	mining
1	128.401	91.741	1.400	0.169	mining
2	0.000	42.362	0.000	1.000	mining
3	234.235	185.312	1.264	0.213	mining
4	0.000	42.362	0.000	1.000	mining
5	0.000	42.362	0.000	1.000	mining
6	0.000	42.362	0.000	1.000	mining
Observations: 71; RMSE: 40.9; Adj. R <sup>2</sup> : 0.304365; Within R <sup>2</sup> : 0.4					
-5	-3041.179	5994.069	-0.507	0.615	financial
-4	-2556.689	5141.231	-0.497	0.622	financial
-3	-2556.689	5141.231	-0.497	0.622	financial
-2	-2556.689	4844.475	-0.528	0.601	financial
0	-6034.354	10065.177	-0.600	0.552	financial
1	-6301.555	10161.886	-0.620	0.539	financial
2	-3047.732	10172.351	-0.300	0.766	financial
3	-22858.162	27949.870	-0.818	0.419	financial
4	-12805.839	15063.349	-0.850	0.401	financial
5	-1672.984	4400.613	-0.380	0.706	financial
6	-2579.063	4302.799	-0.599	0.553	financial
7	-7737.188	12903.451	-0.600	0.552	financial
Observations: 84; RMSE: 13,670.2; Adj. R <sup>2</sup> : -0.514666; Within R <sup>2</sup> : 0.155592					
-5	0.000	6880.141	0.000	1.000	military
-4	0.000	4168.205	0.000	1.000	military
-3	0.000	4168.205	0.000	1.000	military
-2	0.000	4107.984	0.000	1.000	military
0	-49.367	4110.559	-0.012	0.990	military
1	6853.402	3944.484	1.737	0.084	military
2	7227.044	2964.681	2.438	0.016	military
3	8280.215	6397.863	1.294	0.197	military
4	4394.735	4457.100	0.986	0.325	military
5	5944.073	3509.391	1.694	0.092	military
6	21951.242	13253.524	1.656	0.099	military
7	368.881	4478.729	0.082	0.934	military
Observations: 264; RMSE: 7,194.8; Adj. R <sup>2</sup> : 0.334708; Within R <sup>2</sup> : 0.193156					

Time to treatment	Estimate	SE Robust	t value	p value	model
-5	648.603	3072.085	0.211	0.833	information
-4	371.084	2543.219	0.146	0.884	information
-3	-1572.155	2621.190	-0.600	0.549	information
-2	-735.684	2639.404	-0.279	0.781	information
0	-4070.439	2800.672	-1.453	0.147	information
1	-2434.882	2581.476	-0.943	0.346	information
2	-2454.083	3142.501	-0.781	0.435	information
3	-3189.051	3345.509	-0.953	0.341	information
4	462.809	4555.298	0.102	0.919	information
5	2144.739	5550.884	0.386	0.699	information
6	15396.625	15155.039	1.016	0.310	information
7	-8372.805	7150.087	-1.171	0.242	information
Observations: 538; RMSE: 14,407.6; Adj. R <sup>2</sup> : 0.29722; Within R <sup>2</sup> : 0.077183					
-5	-113.606	1079.602	-0.105	0.916	culture
-4	-87.213	874.892	-0.100	0.921	culture
-3	-530.533	929.346	-0.571	0.569	culture
-2	-644.151	823.814	-0.782	0.436	culture
0	-1496.915	979.485	-1.528	0.129	culture
1	-1416.675	1197.841	-1.183	0.239	culture
2	-1164.563	2132.219	-0.546	0.586	culture
3	-1970.155	3541.405	-0.556	0.579	culture
4	-2463.425	2461.037	-1.001	0.319	culture
5	-3681.858	3202.353	-1.150	0.252	culture
6	-5097.045	4703.126	-1.084	0.280	culture
7	-9059.766	9061.559	-1.000	0.319	culture
Observations: 216; RMSE: 6,545.1; Adj. R <sup>2</sup> : -0.171086; Within R <sup>2</sup> : 0.039141					
-5	-3221.697	4792.265	-0.672	0.502	utilities
-4	-2817.171	4475.386	-0.629	0.529	utilities
-3	-3964.548	4749.032	-0.835	0.404	utilities
-2	-839.616	4087.561	-0.205	0.837	utilities
0	6102.767	6356.871	0.960	0.338	utilities
1	9829.300	7652.023	1.285	0.200	utilities
2	5978.668	5213.460	1.147	0.252	utilities
3	4502.161	6401.394	0.703	0.482	utilities
4	16938.124	11546.365	1.467	0.143	utilities
5	-222.302	2156.890	-0.103	0.918	utilities
6	-1107.194	2998.185	-0.369	0.712	utilities
7	-2025.873	1166.324	-1.737	0.083	utilities
Observations: 623; RMSE: 13,981.7; Adj. R <sup>2</sup> : 0.252979; Within R <sup>2</sup> : 0.163682					

Time to treatment	Estimate	SE Robust	t value	p value	model
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Table 6: OLS estimation, Dep. Var.: contract value sum; Fixed-effects: INN: 10, Year: 12;  
Standard-errors: Heteroskedasticity-robust

## E Coefficients for model with number of donations

Time to treatment	Estimate	SE Robust	t value	p value	model
-5	-3911.010	4860.681	-0.805	0.421	donation_count_1
-4	-3325.714	4809.718	-0.691	0.489	donation_count_1
-3	1204.213	5088.169	0.237	0.813	donation_count_1
-2	4760.804	5250.906	0.907	0.365	donation_count_1
0	19892.265	4790.647	4.152	0.000	donation_count_1
1	40847.684	10302.121	3.965	0.000	donation_count_1
2	36475.622	9427.366	3.869	0.000	donation_count_1
3	29715.198	9528.417	3.119	0.002	donation_count_1
4	31136.661	8777.147	3.547	0.000	donation_count_1
5	21681.711	7791.742	2.783	0.005	donation_count_1
6	22898.001	8368.538	2.736	0.006	donation_count_1
7	13367.711	9766.844	1.369	0.171	donation_count_1
N: 17,219; FE: INN: 1,435, Year: 12; RMSE: 31,135; Adj. R <sup>2</sup> : 0.160499; Within R <sup>2</sup> : 0.011244					
-5	-14698.424	11056.977	-1.329	0.184	donation_count_2
-4	-11271.433	12433.529	-0.907	0.365	donation_count_2
-3	-11452.896	11837.301	-0.968	0.333	donation_count_2
-2	-4107.419	11562.022	-0.355	0.722	donation_count_2
0	6963.530	12689.673	0.549	0.583	donation_count_2
1	45449.763	17674.690	2.571	0.010	donation_count_2
2	33402.804	18298.728	1.825	0.068	donation_count_2
3	7874.322	10071.602	0.782	0.434	donation_count_2
4	30916.791	19510.250	1.585	0.113	donation_count_2
5	16291.784	16958.667	0.961	0.337	donation_count_2
6	51120.860	34317.658	1.490	0.136	donation_count_2
7	27930.912	25969.436	1.076	0.282	donation_count_2
N: 10,235; FE: INN: 853, Year: 12; RMSE: 17,160.3; Adj. R <sup>2</sup> : 0.192608; Within R <sup>2</sup> : 0.01536					
-5	53773.487	47847.589	1.124	0.261	donation_count_3
-4	33940.356	30948.660	1.097	0.273	donation_count_3
-3	-4452.656	33219.655	-0.134	0.893	donation_count_3
-2	-316.926	34160.523	-0.009	0.993	donation_count_3
0	18781.485	27664.242	0.679	0.497	donation_count_3
1	71589.158	31160.880	2.297	0.022	donation_count_3
2	62046.828	39707.404	1.563	0.118	donation_count_3
3	96663.012	53460.908	1.808	0.071	donation_count_3
4	53909.463	34161.679	1.578	0.115	donation_count_3
5	237127.426	136821.890	1.733	0.083	donation_count_3
6	-11688.857	52209.545	-0.224	0.823	donation_count_3
7	1858.738	39838.254	0.047	0.963	donation_count_3

Time to treatment	Estimate	SE Robust	t value	p value	model
N: 9,407; FE: INN: 784, Year: 12; RMSE: 46,861.6; Adj. R <sup>2</sup> : 0.354433; Within R <sup>2</sup> : 0.150009					
-5	889.674	93439.731	0.010	0.992	donation_count_4
-4	725.329	59144.127	0.012	0.990	donation_count_4
-3	2556.731	43027.420	0.059	0.953	donation_count_4
-2	3157.833	39170.226	0.081	0.936	donation_count_4
0	1028.430	39163.762	0.026	0.979	donation_count_4
1	128665.050	86958.557	1.480	0.139	donation_count_4
2	45163.351	31503.036	1.434	0.152	donation_count_4
3	45803.007	31482.577	1.455	0.146	donation_count_4
4	38601.355	41314.511	0.934	0.350	donation_count_4
5	114371.626	83639.547	1.367	0.172	donation_count_4
6	50712.515	36201.794	1.401	0.161	donation_count_4
7	3320.907	7818.716	0.425	0.671	donation_count_4
N: 9,252; FE: INN: 771, Year: 12; RMSE: 38,180.1; Adj. R <sup>2</sup> : 0.305215; Within R <sup>2</sup> : 0.059444					

Table 7: OLS estimation, Dep. Var.: contract value sum; Standard-errors:  
Heteroskedasticity-robust

## F Coefficients for income model

Estimate	SE Robust	t value	p value	Time to treatment	model
-2575.530	2484.745	-1.037	0.300	-5	EarningsQ1
-1798.506	2273.577	-0.791	0.429	-4	EarningsQ1
-2584.322	3346.091	-0.772	0.440	-3	EarningsQ1
-119.728	3235.108	-0.037	0.970	-2	EarningsQ1
14276.891	6693.924	2.133	0.033	0	EarningsQ1
22955.606	7307.165	3.142	0.002	1	EarningsQ1
12094.091	5517.050	2.192	0.028	2	EarningsQ1
7379.701	7352.893	1.004	0.316	3	EarningsQ1
5925.002	5251.760	1.128	0.259	4	EarningsQ1
126.937	3926.001	0.032	0.974	5	EarningsQ1
1190.735	4539.622	0.262	0.793	6	EarningsQ1
-587.940	8149.765	-0.072	0.942	7	EarningsQ1
N: 4,703; FE: INN: 392, Year: 12; RMSE: 42,402.9; Adj. R <sup>2</sup> : 0.19594; Within R <sup>2</sup> : 0.048212					
-2571.950	9935.325	-0.259	0.796	-5	EarningsQ2
-2661.371	8429.938	-0.316	0.752	-4	EarningsQ2
-2086.605	7921.527	-0.263	0.792	-3	EarningsQ2
-844.475	7883.749	-0.107	0.915	-2	EarningsQ2
13632.852	7239.592	1.883	0.060	0	EarningsQ2
38788.287	28288.502	1.371	0.170	1	EarningsQ2
26811.642	19304.522	1.389	0.165	2	EarningsQ2
814.743	9132.828	0.089	0.929	3	EarningsQ2
487.584	9629.597	0.051	0.960	4	EarningsQ2
-706.518	12016.558	-0.059	0.953	5	EarningsQ2
-962.516	14805.835	-0.065	0.948	6	EarningsQ2
-1325.877	1607.878	-0.825	0.410	7	EarningsQ2
N: 4,691; FE: INN: 391; Year: 12; RMSE: 97,785.6; Adj. R <sup>2</sup> : 0.137167; Within R <sup>2</sup> : 0.022767					
-4435.305	5392.084	-0.823	0.411	-5	EarningsQ3
-4406.789	4923.747	-0.895	0.371	-4	EarningsQ3
-5337.870	4613.736	-1.157	0.247	-3	EarningsQ3
8425.570	8941.431	0.942	0.346	-2	EarningsQ3
17157.101	6530.633	2.627	0.009	0	EarningsQ3
32283.362	9302.372	3.470	0.001	1	EarningsQ3
23996.411	9075.792	2.644	0.008	2	EarningsQ3
27599.593	9985.069	2.764	0.006	3	EarningsQ3
14709.527	6328.336	2.324	0.020	4	EarningsQ3
24093.393	9488.377	2.539	0.011	5	EarningsQ3
26944.319	11879.313	2.268	0.023	6	EarningsQ3
20573.867	14179.917	1.451	0.147	7	EarningsQ3

Estimate	SE Robust	t value	p value	Time to treatment	model
N: 4,703; FE: INN: 392, Year: 12; RMSE: 63,581.4; Adj. R <sup>2</sup> : 0.207756; Within R <sup>2</sup> : 0.033124					
-4358.356	14274.924	-0.305	0.760	-5	EarningsQ4
-3028.916	14570.951	-0.208	0.835	-4	EarningsQ4
7668.176	16203.278	0.473	0.636	-3	EarningsQ4
4591.130	14788.850	0.310	0.756	-2	EarningsQ4
25443.851	13146.192	1.935	0.053	0	EarningsQ4
81532.706	20743.145	3.931	0.000	1	EarningsQ4
86135.594	26059.267	3.305	0.001	2	EarningsQ4
84266.449	30299.619	2.781	0.005	3	EarningsQ4
119414.750	30931.211	3.861	0.000	4	EarningsQ4
115230.371	35978.554	3.203	0.001	5	EarningsQ4
96378.931	31489.827	3.061	0.002	6	EarningsQ4
48353.363	34214.194	1.413	0.158	7	EarningsQ4
N: 4,691; FE: INN: 391, Year: 12; RMSE: 156,493.1; Adj. R <sup>2</sup> : 0.2738; Within R <sup>2</sup> : 0.060178					

Table 8: OLS estimation, Dep. Var.: contract value sum; Standard-errors:  
Heteroskedasticity-robust

