From Welfare to Workfare: The Impact of the Hungarian Public Work Program on Recipients' Health

by

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Abstract

This paper investigates the impact of the Hungarian Public Work Program (PWP) on participants' overall well-being, aiming to provide a comprehensive assessment of public work program. Leveraging the panel of linked administrative data Admin3, a wide-ranging dataset from the Databank of the Centre for Economic and Regional Studies (KRTK) encompassing a 50% random sample of the Hungarian population, I compare a pooled ordinary least square (OLS) model to various fixed effects specifications, to examine potential effects on the health outcomes of public workers. I perform heterogeneity tests on employment status, sex, age, and residence.

Using a two-way fixed effects model, I find that enrolment in the Hungarian Public Work Program has positive and significant effects on the use of outpatient and inpatient care compared to unemployment while presenting no significant differences compared to the presence in the primary labour market.

By undertaking a thorough examination that surpasses the conventional evaluation criteria of income and employment, this research contributes to a more comprehensive understanding of public work programs. Specifically, it sheds light on the association between direct public employment programs and health, highlighting an often-overlooked dimension of labour market policies. The empirical evidence presented herein aims to inform future policy decisions on labour market interventions in Hungary and beyond.

Keywords: Workfare, Public Work Program, Health, Hungary

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I. Introduction

In recent decades the European Welfare System has undergone a profound transformation, marked by a shift from traditional Welfare States to an emerging model known as Workfare States. This transition has been characterized by an increasing emphasis on labour market activation policies (ALMPs), where social welfare programs aim to provide financial assistance while encouraging recipients' active engagement in the workforce. During the year 2015, an average of 0.53% of the OECD countries' GDP was dedicated to policies of this nature (Fallesen et al. 2018). As part of this broader transformation, and embedded in its particular historical context, Hungary implemented a workfare program in 2009, heavily reformed in 2011, to increase labour force participation and reduce dependency on social benefits. In this paper my purpose is to understand the impact on the health of those who participated in the program, stimulating further research and promote the debate on this crucial yet understudied dimension of public work programs (PWPs).

Public work programs represent a significant departure from traditional welfare schemes, as they introduce a mandatory work requirement for eligible individuals. Participants are required to engage in public sector employment or community-based projects for a specified period, receiving a modest wage in return (Vidra 2018). Despite the diversity of PWPs worldwide, all claim to empower individuals, enhance their skills, and improve their economic prospects while simultaneously addressing the societal challenges associated with unemployment and welfare dependency (Koltai 2015).

While there is extensive research on the PWPs effects on employment and wages, with positive (Escudero et al. 2018) and negative (Card, Kluve, and Weber 2017) results being found, there are limited studies on their effects on the overall well-being of participants, specifically concerning their health outcomes. This knowledge gap is noteworthy, as understanding the potential health implications of participating in PWPs is crucial for evaluating programs' effectiveness and ensuring the well-being of individuals who engage with them. Addressing individuals' health is not only a matter of morality but also holds economic implications. Mental health issues, for instance, have been estimated to account for a substantial economic burden, reaching up to 3-4% of the European Union's GDP (Barnay, 2015). Furthermore, the World Health Organization has projected that the global cost of lost productivity resulting from these issues could reach approximately $6 trillion by 2030 (Belloni, Carrino, & Meschi, 2022).

Therefore, in this paper I ask what the impact is of participating in public work programs on participants' health. By studying the Hungarian PWP, my goal is to uncover potential effects of this welfare-to-work transition on the well-being of program beneficiaries. Moreover, I aim to contribute to the broader discourse on the Workfare State model and its implications for public health while providing valuable insights for policymakers, stakeholders, and researchers interested in labour market activation programs and social welfare reforms. The significant shift in the Hungarian social policies, particularly since 2010, marked by substantial cuts in the welfare system and the prioritization of public works over alternative Active Labour Market Policies (Scharle and Szikra 2015), positions Hungary as a distinctive and essential case study in the transition from welfare to workfare.

Studying this relationship is particularly relevant given the characteristics of the Hungarian PWP. Most public workers in Hungary are engaged in elementary occupations, which typically involve manual or physical labour and do not require prior skills (Szabó 2022). Moreover, these workers receive wages below the national minimum wage and have experienced significant reductions in their social allowances (Scharle and Szikra 2015). Therefore, the effect of engaging in the program is ambiguous.

The remainder of this paper is structured as follows: in Chapter II, I provide a comprehensive literature review on Public Work Programs and the relationship between employment, unemployment, and well-being.

In Chapter III, I offer background information on the socioeconomic context of post-communist Hungary, tracing its transition from a specific post-communist welfare model to a workfare-based society. In Chapter IV, I describe the Hungarian Public Work Program, along with an examination of the workers who participate in the program.

In Chapter V, I present the data used to answer the research question, involving merging the Admin3 dataset from the Databank of the Centre for Economic and Regional Studies (KRTK) with web-scraped information about the Hungarian districts. In Chapter VI, I describe the methodology employed, advocating for the superiority of the fixed effects model in capturing the causal relationship between public work participation and health outcomes compared to a pooled OLS.

In Chapter VII, I present and discuss the main results, followed by heterogeneity tests in Chapter VIII. After incorporating individual and time-fixed effects into the analysis, the findings reveal a tenuous correlation between participation in public work programs and health outcomes, with statistically significant results observed only concerning the use of outpatient care. I find that, on average, individuals involved in public works use outpatient care 0.16 times less per month. The tests of heterogeneity demonstrate statistically significant variations across different groups. Of significant importance, my findings indicate that the positive impact of the PWP is observed exclusively in the comparison between public workers and unemployed individuals. When contrasting these two cohorts, participation in public works is associated with a mean decrease of 1.36 monthly outpatient care visits and a mean reduction of 2.9 inpatient care days per month.

The concluding remarks are provided in Chapter IX, accompanied by policy recommendations in Chapter X.

II. Literature Review

a. Active Labour Market Policies

Active Labour Market Policies (ALMP) play a crucial role in labour market policies, particularly in developed countries, to reduce long-term unemployment by preventing skill depreciation and providing individuals with the necessary skills to secure employment in the primary market (Carling and Richardson, 2004). However, the effectiveness of these policies remains a subject of debate. A comprehensive meta-analysis conducted by Kluve (2010) across 19 European countries found that the success of ALMP depends more on the specific type of program implemented rather than economic or institutional factors. The study concluded that wage subsidies and programs offering assistance in job search, along with sanctions when necessary, exhibit notable effectiveness. In contrast, direct employment programs yielded negative impacts on participants' employment probabilities (Kluve, 2010). Similar findings were observed by Bown and Freund (2019) when extending the analysis to other advanced industrial economies. This differentiation among various types of ALMP is particularly significant, considering that public work programs were the labour market policy favoured in Hungary.

The extensive literature examining the impact of Active Labour Market Policies (ALMPs) on labour market outcomes presents divergent findings. Regarding employment outcomes, Eichler and Lechner (2002) conducted a study in the east German state of Sachsen-Anhalt and found that participation in Public Work Programs (PWPs) significantly reduces the probability of unemployment after program completion. However, they noted that concerning women, this effect is primarily due to higher rates of labour force withdrawal. In contrast, Kraus, Puhani, and Steiner (2000) analysed the same PWPs and concluded that participating in PWPs is associated with a lower likelihood of re-employment in the primary labour market compared to the probabilities of those who remain unemployed. These discrepancies may arise from differences in sample size, geographic coverage, and control for variations in the duration of participation in PWPs (Kraus, Puhani, & Steiner, 2000).

ALMPs have received significant attention in the Nordic countries due to their long-standing tradition and substantial investment in such programs (Kluve, 2010). Carling and Richardson (2004) employed hazard regression analysis to investigate the effectiveness of eight ALMPs in Sweden. Their findings suggest that programs promoting subsidised work and in-job training are more successful in reducing the duration of unemployment compared to those relying on classroom-based approaches, even though the latter is prevalent. Moreover, Carling and Richardson (2004) observed that the timing of worker placement within the program does not significantly impact the results. These conclusions hold across individuals with diverse skills and demographic characteristics. Sianesi (2004, 2008) confirmed these findings using propensity score matching in the Swedish context. However, the author noted that, due to the institutional setting in Sweden, where participation in ALMPs entitles individuals to prolonged access to the unemployment benefits system, a notable proportion of enrolments are motivated by the desire to extend unemployment benefits. Jespersen, Munch, and Skipper (2008) identified similar patterns in Denmark, where job training programs demonstrated positive results on individual employment and earnings, while classroom training programs exhibited less favourable outcomes. In summary, programs that provide participants with opportunities to acquire skills and experience within environments that mirror the primary labour market tend to yield positive results, while those that fail to adequately prepare individuals for formal employment often yield negative outcomes.

These results shed light on the effectiveness of ALMP programs concerning labour market outcomes. However, it is crucial to consider other dimensions when evaluating labour market policies. Research examining the impact of PWPs on non-labour market outcomes has been conducted, particularly in developing countries. Ravi and Engler (2015) investigated the effects of India's National Rural Employment Guarantee Scheme (NREGS) on food security, savings, and health outcomes. Employing a triple difference estimation with groups matched on propensity scores, the authors found significant positive impacts of the program in reducing extreme poverty, improving food security, and increasing savings. Notably, the program exhibited favourable effects on the mental health outcomes of participants, as measured by a composite indicator encompassing emotional and physical dimensions. Beegle, Galasso, and Goldberg (2017) explored the impact of Malawi's PWP on food security using a randomized controlled trial that leveraged oversubscription at both the village and household levels. However, the findings revealed divergent outcomes compared to the NREGS program, potentially attributed to the relatively low additional income provided by Malawi's program compared to the minimum wage offered by NREGS. PWPs also serve as crucial safety nets, enabling workers to transition into preferred occupations (Zimmermann, 2020) and households to provide their members with higher levels of education (Debela and Holden, 2014). In developed countries, the analysis of these programs' impact on non-labour market outcomes is less extensive, given their unique focus on improving employment prospects. However, Fallensen et al. (2018) found positive effects of ALMPs on the crime rate in Denmark, with a significant reduction in property crimes.

b. Employment, Unemployment and Health Outcomes

While the literature on the impact of ALMPs on individuals' health, especially regarding PWPs in developed countries, remains limited, extensive research has explored the relationship between employment status and health outcomes. Barnay (2015), in a review of

European studies, concludes that favourable working conditions and job stability are associated with improved physical and mental health, whereas non-employment, over-employment, and retirement are detrimental health outcomes. However, establishing a direct and unequivocal link between employment and health is challenging. On the one hand, employment provides individuals with better socioeconomic conditions, enabling access to improved lifestyles and healthcare services. On the other hand, adverse working conditions can detrimentally affect workers' health, particularly when these conditions do not align with their preferences (e.g., working hours, contract types, workplace hierarchies, and autonomy). Nonetheless, the findings support the argument that formal employment is associated with positive physical and mental health outcomes, while non-employment and precarious work negatively impact individuals' well-being (Barnay, 2015). These results hold particular relevance considering the conditions and nature of work performed by public workers in Hungary, as further elaborated in subsequent chapters.

The literature also highlights the existence of heterogeneity in the results across various dimensions. Michaud, Crimmins, and Hurd (2016) study the effects of job loss on health, focusing on individual layoffs. Using propensity score matching based on nearest neighbour analysis, the authors examine data from a U.S. panel survey conducted between 2006 and 2008. Their study reveals that the reasons for job loss have varying impacts on health outcomes. While individuals who experience job loss due to business closure do not exhibit significant health effects, those who become unemployed due to layoffs demonstrate deteriorating health outcomes. The authors suggest that psychological stress and a loss of confidence are possible channels underlying these differences (Michaud et al., 2016). A similar mechanism may apply to the PWPs in Hungary, as participants often face stigmatization and negative social perceptions regarding the nature of the work performed (Vidra, 2018).

Belloni, Carrino, and Meschi (2022) similarly studied these heterogeneous results exploiting changes in job quality in the United Kingdom between 2009 and 2016. Their study reveals that different job conditions contribute to health outcomes for men and women. Specifically, women's mental health improves when their skills, autonomy, and working time requirements are met, albeit with variations based on age. In contrast, men place a higher value on career progression opportunities. The authors further find that improvements in working conditions benefit more older workers (Belloni, Carrino, and Meschi, 2022). Jung et al. (2022) employ a triple difference-in-differences approach combined with propensity score matching on Australian survey data. Their findings indicate that both men and women experience job stress, with the impact being significantly stronger among female workers, while job insecurity primarily affects women. Barnay (2015) reports analogous differences, highlighting that male workers are more sensitive to task-related aspects and the pride derived from their work, whereas female workers' health is more responsive to training, motivation, and social support at the workplace. However, factors such as effort, decision power, and justice are globally associated with workers' health conditions (Barnay, 2015).

The literature examining the impact of unemployment on health also lacks consensus, which can be due to the challenges of establishing the direction of causality. Gordo (2006), using longitudinal data from Germany, finds that long-term unemployment negatively affects individuals' satisfaction with their health, whereas short-term unemployment only affects men. However, irrespective of the duration of unemployment, both men and women experience an increase in health satisfaction following reemployment. In a broader context, Adams et al. (2003) establish a significant relationship between socioeconomic status and physical and mental health conditions. However, it is relevant to note that their findings have limited external validity as they rely on a panel dataset of American individuals aged 70 or older, which represents a specific segment of the population with a peculiar healthcare support system. In contrast, Schmitz (2011), using the same data as Gordo (2006) but employing fixed-effects models and employing plant closure as an exogenous source of unemployment, finds no significant impact of unemployment on health across different measures and subgroups. As most public workers were previously employed, my research can contribute to bridging this gap in the literature.

In summary, the literature on ALMPs, specifically PWPs, and the relationship between employment status and health outcomes is extensive but lacks integration. This gap is particularly significant considering that PWPs represent a distinct form of employment with unique working conditions.

III. The Hungarian Transition from Welfare to Workfare

Hungary, as a former communist country, underwent a transition to an open market economy in 1989. The country's journey to join the European Union, which began in 1994 and ended in 2004, further shaped its unique Social Welfare model.

The shift from a centrally planned economy to an open market system resulted in a severe economic crisis in Hungary. During this period, approximately 1.2 million jobs were lost, representing around 20% of the total employment, and were not effectively replaced in the following years (Vidra, 2018). Aiming to mitigate the impact of job losses, the government implemented, throughout the 1990s, various measures that led to a decline in labour market participation, such as early retirement, parental leave, disability pensions, and substantial unemployment benefits (Vidra, 2018; Vanhuysse 2004). Nevertheless, these policy changes occurred alongside the introduction of neoliberal reforms promoted by the European Union and the International Monetary Fund. Consequently, Hungary's Social Welfare model exhibited a distinct blend of contradictory elements, marked simultaneously by significant levels of solidarity and liberalization of social policies (Aidukaite, 2011).

Another consequence of the policy decisions made during the transition period was the exacerbation of regional disparities in Hungary, which has significant implications for understanding the implementation of the PWP and Hungary's shift from welfare to workfare. As part of the transition, a decision was made to establish a highly fragmented municipal system, delegating a substantial portion of welfare responsibilities, including social assistance and essential social services, to the local level. Consequently, poorer regions faced challenges in providing adequate social support and services, often resulting in lower quality provisions in the areas where they were more required (Ágota Scharle and Dorottya Szikra, 2015).

The Bokros austerity package introduced in 1996 resulted in the abolition, reduction, or stricter eligibility criteria for certain social benefits. However, it was not until the election of the most recent Conservative government in 2010 that a significant shift from a Welfare Social model to a Workfare agenda took place. In response to the financial strain and reduced labour market activity caused by the transition policies, several measures were introduced in the early 2000s to decrease social assistance and promote a greater activity rate. These measures primarily involved reducing the duration and amount of unemployment benefits alongside some Active Labour Market Policies (ALMP). However, limited monitoring and targeting characterized these ALMPs. Notably, two significant changes carried out in the 2000s laid the groundwork for the comprehensive reforms implemented by the Fidesz-KDNP government after 2010. The first occurred in 2000 during Prime Minister Orbán's first term in office under the Fidesz Government. This reform introduced means-tested unemployment assistance, reducing its value, and merging it with the social assistance program. Eligibility for this assistance became conditional on the lack of employment, thereby rendering ineligible the working poor individuals. Importantly, claimants were required to engage in 30 days of Public Work to be eligible. The Socialist government deepened this reform in 2009 by categorizing unemployment assistance recipients into two groups: those capable of working and those unable to do so. While the latter group got the unemployment benefit remained unchanged and the work requirement removed, the former saw the unemployment assistance considerably reduced. Additionally, the work requirement for the first group was extended to 90 days of public work per year, compensated at the minimum wage rate. Additionally, there was a significant increase in funding for such programs, representing the initial major push toward a workfare system (Duman and Ágota Scharle, 2011).

In 2010, following the election of the Fidesz government, substantial and transformative reforms were implemented in the Hungarian social model, with a radical shift towards the workfare ideology. This shift was explicitly incorporated into the Constitution in 2011 (Duman and Ágota Scharle, 2011). Concurrently, social assistance and public works suffered significant changes alongside a new Labour Code. Initially, the insured unemployment benefit underwent vast cuts in value and coverage duration, with a rise in its contribution requirement. Additionally, the law expanded the definition of a suitable job to include positions that required skills below the recipient's level of education or their previous job, accompanied by stricter penalties for rejecting those offers. Moreover, the government created the Public Work Program, a reform of the “Pathway to Work Program” introduced in 2009 by the socialist government, significantly expanding public works while lowering their wage (below the national minimum wage) and centralizing its administration (Vidra 2018). This investment in the PWP came with disinvestment in social assistance. In addition to the mentioned reductions in the insured unemployment benefit, the government implemented more stringent regulations for receiving unemployment assistance. These regulations included stricter requirements for engaging in public or community work, a decrease in the nominal value of the transfer, and the extension of behavioural conditions for eligibility. As outlined by Duman and Scharle (2011), these policies resulted in increasingly unequal access to these benefits, a bigger proportion of unemployed individuals without adequate support, an increase in the poverty rate, and a reduced capacity of social assistance in alleviating poverty.

A significant aspect of the PWP in Hungary pertains to its regional variations and discriminatory biases (Duman and Scharle 2011; Vidra 2018). These issues have become more prominent due to the tightening and reduction of social assistance, alongside the increasing emphasis on public work as a primary alternative to other AMLPs. Despite the centralization of PWP administration, municipalities continue to serve as the primary employers of public workers. The program implementation differed across regions based on the perspectives of local mayors, with some viewing it primarily as a source of cheap labour rather than a means of reintegration (Koltai 2015). The result was the stigmatization of public workers and the regional disparities of these opportunities. Regarding discrimination, it is important to highlight that local governments are not obligated to provide public work opportunities to all unemployed individuals within their jurisdiction. Consequently, many people cannot fulfil the 30 days of public work required to receive social assistance. Reports have indicated that specific groups, particularly the Roma population, are intentionally excluded from the program in municipalities governed by extreme-right mayors, effectively denying them access to any form of welfare provision (Duman and Scharle 2011).

In summary, the Hungarian social model underwent a profound transformation in the latter half of the previous decade, transitioning from a traditional welfare approach to a robust workfare paradigm. This significant shift sets the stage for an in-depth exploration of one of the pillars of the Hungarian workfare model: the Public Work Program. The following chapter will delve into its intricacies and unique aspects, shedding light on its framework and distinct characteristics.

IV. The Hungarian Public Work Program

The concept of workfare in Hungary did not start in the last decade. Public work initiatives started towards the end of the 1990s as part of Hungary's political and economic transition from communism to a market-based economy. However, it was not until 2009, with the creation of the "Pathway to Work", that a concrete and organized Hungarian Public Work Program emerged. In 2011, the new government introduced several legislative changes that reformed the program, expanding it significantly (Vidra 2008). Hungary public expenditure on direct job creation as a percentage of GDP reflects its commitment to this initiative. According to statistics from the OECD, between 2011 and 2018, Hungary consistently exceeded the OECD average in this type of public spending, with the peak occurring in 2016 when more than 0.7% of GDP was allocated to direct job creation in Hungary, while the OECD average remained consistently below 0.1%. The dimension of the program is equally captured by the almost 700 thousand people employed in it between 2011 and 2019 (Szabó, 2022).

There is a mismatch between the objectives and the implementation of the Hungarian PWP. The goal of public work programs is to facilitate the transition of unemployed individuals to the primary labour market. However, these programs primarily serve as public employment, often used by municipalities to carry out specific tasks. Koltai et al. (2019) highlight the significance of public workers in ensuring the smooth functioning of essential activities like the preservation of public spaces and the provision of sociocultural and educational services. Estimations by Szabó (2022), based on the Hungarian State Treasury (MÁK) administrative database, support these claims. In 2014, 80% of public workers were engaged in elementary occupations[1], a share that remained relatively stable from 2011 to 2017. Rather than

[1] Occupation FEOR 9, according to the Hungarian Standard Classification of Occupations. This category concerns occupations that do not require prior qualifications and include, among many others, activities such as cleaning, manual work, garbage collection, and simple farming, fishing, and mining tasks.

equipping workers with the skills demanded by the primary labour market, it appears that public workers primarily fulfil the need for municipal workers to provide essential public services. These jobs often require no specific qualifications, leaving workers without the opportunity to acquire such skills. It is then not surprising that both Koltai et al. (2019) and Szabó (2022) find high levels of "locked-in" participants, with most workers staying in the PWP without moving to the primary labour market due to a mismatch in demand and supply of skills (Koltai et al. 2019). Nonetheless, in both cases, the authors report an improvement over time.

Between 2011 and 2019, most public workers were between 23 and 57 years old, with a relatively uniform distribution among different cohorts. Full-time employment was predominant among these workers, and a significant portion of them remained in the program for over a year, with an average duration surpassing 18 months, aligning with the previously mentioned locked-in effect. As anticipated, individuals who regressed from the primary labour market to the PWP held occupations with lower skill requirements, even though a substantial portion of public workers were inactive before joining the program. Another expected finding is that public workers exhibited a higher job turnover, spending less time in each position. In conclusion, despite some improvements over the years, the reality remains that public workers face greater challenges in securing employment within the primary labour market compared to those already employed. Furthermore, even when they do it, they demonstrate a tendency to change jobs more frequently and have shorter tenures in each occupation (Szabó 2022). Despite these challenges, Koltai et al. (2019) argue that public work offers an in-between integration, suggesting that public workers, even though they may face the lock-in effect, become more skilled and perform better at work after joining the program.

For detailed information, consult https://www.ksh.hu/docs/szolgaltatasok/eng/feor08/efeor08.pdf.

The 2011 reform introduced three distinct types of initiatives: “national public work programs”, “micro-regional start model programs”, and “long-term public work programs”. Among these, the “micro-regional start model programs” emerged as the central component of the reform, accounting for most of the allocated resources and specifically targeting less developed districts[2]. These programs primarily involve elementary occupations and play a key role in creating discernible regional variations in the proportion of public workers. In contrast, the “national public work programs” are organized by public entities responsible for delivering essential public services such as infrastructure and public space maintenance and constitute the smallest fraction of the overall PWP investment. Notably, these national programs' budget allocation is not dependent upon the development level of the respective districts. Finally, the “long-term public work programs” target those regions that do not meet the eligibility criteria for the “micro-regional programs” (Szabó 2022).

The distinctive attributes of the Hungarian PWP and of the public workers across various regions reflect the regional socioeconomic disparities that characterize post-communist Hungary. As expected, considering the objectives of the PWP, it is evident that less developed regions experience a higher degree of program implementation. However, beyond the variations in treatment intensity, regional disparities can also be observed in other aspects, particularly regarding the duration of participation in the PWP and the ability to secure employment in the primary labour market.

Szabó (2022) conducted a comprehensive examination of the Public Work Program (PWP) between 2011 and 2019, highlighting the differences in program duration across different regions, directly correlated to their economic performance. The results show significant

[2] The level of development of each district is computed based on a complex indicator. The complex indicator was published by a 2014 Government Decree, and encompasses a range of development dimensions, including social and demographic indicators, housing and living condition indicators, local economy and labour market indicators, and infrastructure and environmental indicators.
A comprehensive description of the criteria and methodology employed to calculate this indicator can be found at: https://net.jogtar.hu/jogszabaly?docid=a1400290.kor.

discrepancies, with a notable difference of more than two years observed between the districts with the shortest and longest median durations of PWP participation. While in the former one, a significant proportion of workers had a short stay in the program, typically less than six months, in the latter, a smoother distribution of observations was observed across different years of program participation, including several individuals who remained in the PWP for more than six years. Overall, the eastern and southern counties of the country exhibit longer durations of public work engagement, coinciding with a higher proportion of public workers in those areas. The job-finding rates equally reflect this geographical disparity, with differences of up to 30% in the time spent in the primary labour market in the year following PW participation between workers in developed and undeveloped regions (Szabó 2022). These findings perfectly mirror the broader regional disparities evident across various socioeconomic dimensions in Hungary[3].

The next chapter focus on the database used in this paper that draws from the same 50% sample of the MÁK database used by Szabó (2022) in the public workers' characterisation I have just presented. Consequently, the information in the current chapter serves as a solid benchmark for the subsequent analysis.

V. Data

I use the Admin3 Database, provided by the Databank of the Centre for Economic and Regional Studies (KRTK) in Hungary. Access to the database was granted through the institute's server. The Admin3 Database consists of an anonymized dataset comprising monthly individual observations.

The primary file encompasses 5,174,040 individuals, randomly selected, that account for approximately 50% of the Hungarian population. These individuals were observed monthly

[3] For a deeper analysis of the Hungarian regional disparities, see https://www.oecd-ilibrary.org/sites/fb3c2183-en/index.html?itemId=/content/component/fb3c2183-en

from January 2003 to December 2017. The main file captures several personal and labour market-specific information. Key variables of interest include age, gender, district of residence, monthly income and working hours, relevant social transfers, and, notably for this study, participation in the Public Work Program. The health-related variables, which serve as the primary outcomes of this study, are derived from the H1 files within the Admin3 Database. These files maintain the same level of individual monthly analysis but span a narrower timeframe from January 2009 to December 2017. The main variables within the H1 files are drug prescription and the use of inpatient and outpatient care. It includes the frequency and cost (in forints) of inpatient and outpatient visits, laboratory and non-laboratory care, and the number of prescriptions. Given that PWP status is observable only from 2011. the sample for this study comprises observations from that point until December 2017.

Evaluating the program's impact on individuals' health requires certain age restrictions. I excluded individuals younger than 16 and older than 55 as of September 2011. This age range restriction was applied as I considered it appropriate to concentrate the analysis on individuals within the relevant age range for this study, concretely excluding those that in the beginning of the period were not legally allowed to work or were too close to the pension age. I perform robustness checks in samples that contain different age ranges. Additionally, I have generated two additional variables to understand the PWP dynamics and employment status within the dataset. The first variable indicates whether an individual has ever participated in the PWP during the period under consideration. The second variable denotes the employment status of individuals. The dataset does not explicitly provide an employment indicator using the ILO definition. Therefore, I applied an identification method in line with prevailing practices among researchers employing this dataset. Accordingly, individuals were classified as employed if they exhibited positive labour income and a discernible employment relationship in each monthly observation. The resulting dataset encompasses 206,553,636 records distributed among 2,717,811 distinct individuals.

To account for differences of development among districts, with a direct impact on the PWP implementation, I merged a dataset containing district information.[4] Relevant to the analysis, this dataset includes a binary variable that identifies whether a district is beneficiary or not (complex indicator below 46.68, the country average)[5].

The descriptive statistics for the main variables are presented in Table A.1. Within the sample, 5,830,887 observations are instances of PWP participation, accounting for approximately 2.82% of the sample. There are 284,549 individuals who participated in PWP for at least 1 month in 2011-2017. Among these individuals, the average duration of participation in the program was approximately 37 months, with the longest observed participation lasting 76 months, encompassing the entire period covered by the sample. Regarding the healthcare variables, focusing on positive observations only, the dataset reveals 36,336,912 instances of outpatient care utilization, concerning 2,475,699 distinct individuals. On average, individuals in the sample used outpatient care approximately 2.5 times per month, with a maximum use of 108 times a month. In terms of inpatient care, specifically financed hospital days, there were 2,813,154 occurrences involving 1,031,187 individuals. The average monthly utilization of inpatient care amounted to approximately 6 days, with the maximum duration recorded as 31 days, representing an entire month. Lastly, the dataset records 48,748,456 instances of prescription drug usage, covering 2,425,494 unique

[4] The information was extracted from the website Wolters Kluwer (https://net.jogtar.hu/), which contains a collection of legal regulations and their period. For this study, I am interested in the Government Decree No 290/2014 of 26 December that classifies the beneficiary districts.

[5] These calculations are from 2014 onwards. However, for my analysis, it serves as a proxy for district development, given the regional disparities of the program mentioned in chapters 2 and 3, and not as an objective measure of funding or work type in each district. Since regional inequalities remained relatively stable throughout the period, I applied the classification to the entire sample (2011 to 2017). For further details regarding the indicator and district classification, refer to footnote 2.

individuals, with an average of approximately 3.3 prescriptions per month. The maximum entry was of 274 prescriptions in a single month.

Table A.2 presents descriptive statistics for observations within and outside the PWP. It is important to note that this comparison is not between individuals who have participated in the PWP with those who have never done it; instead, it compares observations that occurred within the PWP in each respective month with those outside the program. The results reveal that the age distribution of individuals enrolled in the PWP is identical to that of individuals outside the program, with averages of approximately 40.6 and 39.1 years, respectively. However, within those not participating in PW, employed people are on average 40.5 years-old, while unemployed are 36.9 years-old. Furthermore, there is a marginal difference in the number of monthly income days, with PWP participants averaging around 29.1 days compared to approximately 29.3 days for employed non-participants. As expected, significant distinctions arise regarding monthly wages and social transfers received, which align with the characteristics of the PWP discussed in the preceding chapter. Individuals participating in the PWP receive an average monthly wage of 76,727 forints, whereas those employed in the primary labour market receive an average of 213,569 forints/month. Concerning transfers, PW and people employed outside the program differ mainly in Unemployment/Sick transfers, with the formers receiving an average of 25 forints/month, while the later receive an average of 9.6 forints/month.

Lastly, I present the raw disparities in the healthcare variables in (Table A.3). We cannot observe substantial differences between Public Work Program (PWP) participants, individuals employed in the primary labour market, and unemployed individuals. However, noteworthy distinctions are evident in terms of inpatient care. PWP participants have an average of 5 days per month, employed individuals have an average of 4.2 days, and unemployed individuals have an average of 7.35 days.

In the next chapter, I will explain the methodology employed to investigate these preliminary findings while looking to uncover potential causal relationships between Public Work Participation and healthcare outcomes.

VI. Methodology

The objective of my study is to estimate the impact of participating in the Public Work Program (PWP) on healthcare outcomes:

$$\boldsymbol{HealthCare\_Outcome_{it} = \alpha + \beta Public\_Work_{it} + \theta X_{it} + \sigma_{it}} \qquad (1)$$

Where $\boldsymbol{HealthOutcome_{it}}$ is the chosen health variable of the individual $\boldsymbol{i}$ in the month t. In my main results I use the monthly days of Outpatient and Inpatient care used by each person, and their monthly number of prescriptions. $\boldsymbol{PublicWork_{i,t}}$ is a binary variable that take the value 1 if the individual $\boldsymbol{i}$ was participating in the PWP in the month $\boldsymbol{t}$. $\boldsymbol{X_{it-1}}$is a set of controls of the individual $\boldsymbol{i}$ observed in the period $\boldsymbol{t}$ that contains age, sex (1 if the individual is a man), monthly wage, weekly hours worked, occupational group and a set of different social transfers[6].

The primary concern when using equation (1) to make any causal inferences comes from the fact that participating in the PWP is not random. Then, despite the comprehensive data that allows me to use several controls, the Ordinary Least Squares (OLS) estimator is likely inconsistent, given the non-observables that simultaneously affect healthcare outcomes and public work participation. For instance, individuals who struggle with substance addiction are

[6] The occupation group classification used is the two-digit harmonized FEOR, between 2003 and 2017. The social transfers included are benefits related to children, pension, unemployment or sick leave and other types of social allowances.

more likely to face multiple health problems while encountering difficulties in securing employment in the primary labour market, hence more prone to becoming public workers. One way to tackle this omitted variable bias is to include fixed effects (FE), where instead of estimating the relationship between health and PWP participation in levels, I compare their relationship in terms of changes to the mean, within each chosen FE category. This specification allows me to control for any baseline differences across individuals, districts, or years, whether they come from observable or unobservable variables.

For instance, in an individual FE model we get coefficients that capture how much larger the healthcare outcome is, on average, compared to its mean within each individual, where and when a given explanatory variable is higher by one unit compared to its average within each cross-sectional unity.[7] If we consider that the confounders that I cannot control for are indeed time-invariant and affect the levels of the variables and not their change (meaning that, during the period of observation, these confounders will not affect PWP and healthcare outcomes differently), so the estimators are unbiased and capture the impact of PWP on those healthcare outcomes.

To strengthen the estimation model, I have incorporated two additional modifications alongside the fixed effects. The first modification involves introducing an interaction term between the PWP and beneficiary districts. The implementation and characteristics of the PWP in Hungary exhibit a notable geographical differentiation. Consequently, the program's impact is likely to vary depending on the developmental level of each district. By incorporating the interaction term, I aim to capture these regional disparities and disentangle the effects of the PWP between developed and undeveloped regions. The second modification focuses on addressing potential issues of reverse causality by including lags in the

[7] The methodology and coefficient interpretation used is based on the book “Data Analysis for Business, Economics, and Policy” by Gábor Békés and Gábor Kézdi. For more information, visit https://gabors-data-analysis.com.

explanatory variables. Since the dataset comprises monthly individual observations, it is plausible that an individual's health status may influence their labour markets conditions in the same period, such as working hours, wages, or even participation in the PW program. To account for this, I conduct FE regressions with lagged variables spanning 1, 3, 6 and 12 months (as shown in Table A.3; Table A.4; Table A.6). Given that the results exhibit no significant changes across different lag lengths, I employ a 1-month lag. This time frame adequately addresses concerns related to reverse causality while preserving most observations.

Consequently, my baseline regression model is:

$$\boldsymbol{HealthOutcome_{it} = \beta_1 PublicWork_{i,t-1} + \beta_2 BeneficiaryDistrict_{i,t-1} +}$$
$$\boldsymbol{\beta_3 PublicWork_{i,t-1} * BeneficiaryDistrict_{i,t-1} + \theta X_{it-1} + \varepsilon_{it}} \qquad (2)$$

Compared to equation (1), $\boldsymbol{PublicWork_{i,t-1}}$ and $\boldsymbol{X_{it-1}}$ represent the same group of variables, but now observed in the month $\boldsymbol{t-1}$. $\boldsymbol{BeneficiaryDistrict_{i,t-1}}$ is a binary variable that take the value 1 if the individual $\boldsymbol{i}$ was living in a beneficiary district in the month $\boldsymbol{t-1}$**.**

I estimate variations of equation (2) with individual, year and district fixed effects. My preferred specification is a two-way FE model with individual ($\boldsymbol{\alpha_i}$) and year ($\boldsymbol{\lambda_{year}}$) fixed effects. This specification allows me to control for unobserved individual characteristics that are time-invariant (e.g., any previous health condition that leads someone to visit the doctor more frequently, but at the same time makes someone less likely to find a job in the primary labour market) and time-variant characteristics that are constant over individuals (e.g., changes in the Hungarian economic environment that affect both the labour market and the wellbeing of individuals). The presence of these unobserved variables is a plausible scenario, and as such, I posit that the pooled OLS estimator is susceptible to bias and that the two-way

FE estimator fulfils the necessary identification requirements, enabling me to establish causal claims. Therefore, my preferred model specification is:

$$\boldsymbol{HealthCare\_Outcome_{it} = \beta_1 PublicWork_{i,t-1} + \beta_2 BeneficiaryDistrict_{i,t-1} + \beta_3 PublicWork_{i,t-1} * BeneficiaryDistrict_{i,t-1} + \theta X_{it-1} + \alpha_i + \lambda_{year} + \varepsilon_{it}} \quad (3)$$

I clustered the standard errors at the district level, as likely the observations within districts are correlated for reasons that I cannot observe, creating spatial correlation in the error terms. In this way, I allow error terms to be correlated within districts. Clustering the error terms at the district level is also possible due to the number of districts in the data (198), allowing me to have a robust number of clusters[8].

The main coefficients of interest are $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_3}$. If the FE assumptions old, $\boldsymbol{\beta_1}$ captures the impact in the given healthcare outcome of participating in the PWP within each individual, district or year (depending on the specification). $\boldsymbol{\beta_3}$ tell us how the effect of the PWP on individuals' wellbeing differs across districts, depending on their development level.

VII. Results and Discussion

In this chapter, I begin by studying the relationship between public work participation and the monthly utilization of outpatient care. I present the findings from the pooled OLS regression and fixed-effects models at the individual, district, and year levels, and a combination of those. Finally, I extend the analysis to include as dependent variables the monthly use of inpatient care and the monthly number of drugs prescriptions.

a. Outpatient Care

In the data I find a statistically significant association between PWP participation and the monthly use of outpatient care, something common across all my specifications. Starting by

8 To obtain comprehensive guidance on how to address clustering, see Cameron and Miller (2015)

the pooled OLS model (Table 1 – column 1), participating in the PWP is associated, on average, with approximately less 0.19 monthly visits, a coefficient statistically significant at the 0.1% level. The coefficient corresponding to beneficiary districts is not statistically different from 0, meaning that between individuals that do not participate in the PWP, living or not in a beneficiary district does not seem to impact outpatient care use. The interaction term between public work and beneficiary district, on the other hand, is significant at the 5% level, meaning that the average association between participating in the PWP and the monthly use of outpatient care significantly differs between observations living in and out beneficiary districts. Concretely, living in a beneficiary district increases this association approximately by 0.06 times/month.

When running the two-way FE presented in equation (3) (Table 1 – column 5), the PWP coefficient is reduced from -0.1957 to -0.1586, but it stays significant at the 0.1% level. We can conclude that the PWP impacted positively the outpatient care use of individuals who participated in the program, leading to approximately less 0.16 visits to the doctor per month. The interaction term drops in half (from 0.05574 to 0.02919), losing its statistical significance at any considered level. On the other hand, the single beneficiary district coefficient significantly increases in absolute value (from -0.02672 to -0.08489) and becomes statistically significant at the 0.1% level. It is important to note that in a two-way FE model, this is not the average difference between observations in and out the PWP, but rather the average difference of outpatient care compared to its mean value, between observations in and out the PWP, within each individual and year.

While the results demonstrate a statistically significant effect of PWP participation on outpatient care utilization, it is important to note that the magnitude of the coefficient is relatively small. Consequently, it is challenging to confidently assert the actual impact of the program on individuals' well-being. Gaining an understanding of the economic significance of this impact can be achieved by comparing the coefficient of interest with the monthly average number of visits to the doctor by the baseline group. Individuals who neither participate in the PWP nor reside in a beneficiary district exhibit an average monthly doctor visit rate of approximately 2.55 times. A reduction of around 0.16 monthly visits, which corresponds to a 6% decrease in outpatient care utilization compared to the baseline group, suggests a modest rather than a substantial improvement in the well-being of the participants. Nonetheless, this reduction may indicate a positive impact on their health.

b. Inpatient Care

Regarding inpatient care, the initial pooled OLS estimation (Table 2 – column 1) reveals a statistically significant relationship between PWP participation and the number of hospital days covered. On average, participation in the PWP is associated with approximately more 0.63 days per month spent in the hospital. The coefficient is statistically significant at the 0.1% level and suggests a minor improvement in the well-being of public workers. However, after controlling for individual and time fixed effects (Table 2 – column 5), the coefficient turns negative, with a value of -0.1380, and loses its statistical significance across all considered levels. The same pattern holds for the interaction term, which, in the pooled OLS regression, is statistically significant at the 0.1% level with a value of -0.3832 but diminishes to around -0.008 in the two-way FE model, indicating no significant deviation from zero at any level of significance. Hence, the results show that participating in the Hungarian PWP has no effects in the use of inpatient care.

These findings are unsurprising. Although public workers are primarily engaged in elementary occupations, their tasks do not typically involve significant physical strain that could lead to a higher hospitalization rate. Therefore, we do not expect a notable increase in inpatient care. Despite the nature of the Hungarian PWP, there may be positive effects associated with public work participation given the positive links between work and health found in the literature. However, it is important to note that in the main specifications, I compare observations of public workers with both employed and unemployed individuals. This approach may obscure any distinct effects of public work compared to either of these specific groups. In the next chapter, I conduct tests for heterogeneity to examine these potential patterns more closely.

c. Drugs Prescription

A similar pattern is found in the relation between PWP participation and drugs prescription. When considering the pooled OLS estimation (Table 3 – column 1), we observe that, on average, participating in the PWP is associated with more 0.45 monthly prescriptions. The coefficient is statistically significant at the 0.1% confidence level and represents an increase of approximately 14% compared to the average monthly prescriptions of the baseline group, what could be a symptom of the decreasing wellbeing of public workers. Furthermore, based on the OLS estimator, the association between public work and the number of prescribed drugs changes by approximately 0.16 prescriptions per month based on the beneficiary status of the residential district.

Nonetheless, as in the use of inpatient care, this apparent relationship between PWP participation and drugs prescribed disappears when accounting for individual and time fixed effects. Looking at the two-way FE coefficients (Table 3 – column 5), participating in the PWP has no effect in the monthly number of prescriptions, with the coefficient dropping to 0.01 and not being significantly different from 0 at any considered level. The interaction coefficient is reduced to 0.04, and despite remaining statistically significant at the 5% level, it has no economic significance.

Differently from the use of inpatient care, these results provide valuable insights, as one could expect any possible outcome. The lack of statistical significance suggests that engaging in public works does not yield significant changes in the wellbeing of public workers However, it is crucial to acknowledge that these results may mask variations across different population subgroups. To explore the persistence of this seemingly lack of health deterioration in public workers, heterogeneity tests will be conducted in the subsequent chapter.

An important finding arising from the previous estimations is that the inclusion of district and year fixed-effects produces marginal alterations in the coefficients and the R-squared values of the models. Conversely, the incorporation of individual fixed effects leads to substantial changes in the outcomes and results in a notable improvement in the explanatory capability of the model. This observation suggests that a significant portion of the unobserved variables, which may introduce bias in the findings, are individual-specific and remain constant over time, effectively controlled by the selected fixed effects specification. This discovery underscores the robustness of the obtained results.

Table 1 - Outpatient Care

	OLS	Individual FE	Year FE	District FE	Individual and Year FE	Individual and District FE	Individual, Year and District FE
Public Work	-0.1957^{***} (0.0182)	-0.1529^{***} (0.0160)	-0.1990^{***} (0.0183)	-0.1945^{***} (0.0214)	-0.1586^{***} (0.0160)	-0.1525^{***} (0.0160)	-0.1582^{***} (0.0160)
Beneficiary District	-0.02672 (0.0322)	-0.08706^{***} (0.0121)	-0.02678 (0.0322)	0.1818^{***} (0.0441)	-0.08489^{***} (0.0119)	0.1069^{**} (0.0333)	0.1078^{**} (0.0332)
Public Work x Beneficiary District	0.05574^{*} (0.0220)	0.02738 (0.0185)	0.05679^{*} (0.0219)	0.02525 (0.0236)	0.02919 (0.0185)	0.02660 (0.0185)	0.02843 (0.0185)
Constant	2.6778^{***} (0.0397)	1.5517^{***} (0.1082)	2.6742^{***} (0.0392)	2.5795^{***} (0.0395)	4.9841^{***} (0.1497)	1.4953^{***} (0.1100)	4.9260^{***} (0.1501)
N	21,532,380	21,343,061	21,532,380	21,532,380	21,343,061	21,343,061	21,343,061
R^2	0.0275	0.2037	0.0275	0.0320	0.2039	0.2038	0.2039
Baseline Mean	2.551141	2.556536	2.551141	2.551141	2.556536	2.556536	2.556536
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
District FE	No	No	No	Yes	No	Yes	Yes

Notes: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Robust standard errors, in parentheses, are clustered at the district level (198 clusters); The dependent variable is the number of times an individual used outpatient care in the given month; Explanatory variables and controls are lagged 1 month; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section.

Table 2 - Inpatient Care

	OLS	Individual FE	Year FE	District FE	Individual and Year FE	Individual and District FE	Individual, Year and District FE
Public Work	0.6302*** (0.0914)	-0.1506 (0.1501)	0.6506*** (0.0908)	0.6239*** (0.0909)	-0.1380 (0.1506)	-0.1530 (0.1495)	-0.1403 (0.1500)
Beneficiary District	0.04966 (0.0568)	-0.05734 (0.0907)	0.05162 (0.0566)	0.08656 (0.1460)	-0.05282 (0.0909)	0.2403 (0.2369)	0.2463 (0.2370)
Public Work x Beneficiary District	-0.3832*** (0.1044)	-0.002862 (0.1882)	-0.3794*** (0.1040)	-0.4275*** (0.1036)	-0.007997 (0.1885)	-0.003199 (0.1871)	-0.008450 (0.1873)
Constant	5.1879*** (0.2045)	2.9944*** (0.6664)	5.2550*** (0.2049)	5.1908*** (0.2060)	4.8121*** (1.0942)	2.9122*** (0.6766)	4.7344*** (1.1004)
N	1,366,726	1,013,315	1,366,726	1,366,726	1,013,315	1,013,315	1,013,315
R^2	0.0645	0.5223	0.0648	0.0675	0.5224	0.5225	0.5225
Baseline Mean	4.657401	5.203126	4.657401	4.657401	5.203126	5.203126	5.203126
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
District FE	No	No	No	Yes	No	Yes	Yes

Notes: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Robust standard errors, in parentheses, are clustered at the district level (198 clusters); The dependent variable is the number of times an individual used outpatient care in the given month; Explanatory variables and controls are lagged 1 month; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section.

Table 3 - Drugs Prescribed

	OLS	Individual FE	Year FE	District FE	Individual and Year FE	Individual and District FE	Individual, Year and District FE
Public Work	0.4502*** (0.0369)	0.01434 (0.0156)	0.4315*** (0.0362)	0.4691*** (0.0406)	0.01175 (0.0155)	0.01384 (0.0156)	0.01123 (0.0155)
Beneficiary District	-0.05678* (0.0224)	-0.02624* (0.0122)	-0.05897** (0.0224)	-0.009732 (0.0284)	-0.02296+ (0.0122)	-0.01224 (0.0264)	-0.01236 (0.0264)
Public Work x Beneficiary District	0.1663* (0.0707)	0.03774+ (0.0199)	0.1659* (0.0702)	0.1189+ (0.0654)	0.04131* (0.0198)	0.03854+ (0.0199)	0.04214* (0.0198)
Constant	3.2351*** (0.0585)	2.5772*** (0.0832)	3.1582*** (0.0581)	3.2023*** (0.0528)	6.6414*** (0.1414)	2.5715*** (0.0826)	6.6367*** (0.1386)
N	29,495,433	29,283,850	29,495,433	29,495,433	29,283,850	29,283,850	29,283,850
R^2	0.0329	0.3300	0.0337	0.0351	0.3304	0.3300	0.3304
Baseline Mean	2.916962	2.921463	2.916962	2.916962	2.921463	2.921463	2.921463
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	No	Yes	No	Yes
District FE	No	No	No	Yes	No	Yes	Yes

Notes: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Robust standard errors, in parentheses, are clustered at the district level (198 clusters); The dependent variable is the number of times an individual used outpatient care in the given month; Explanatory variables and controls are lagged 1 month; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section.

VIII. Heterogeneity Analysis

In addition to the conducted tests on various specifications in the preceding section, there are potential heterogeneity patterns in the relationship between public work participation and healthcare outcomes. Due to the inherent nature of this relationship, distinct groups may exhibit significant variations in the impact of the PWP. Although controlling for most of these dimensions in my primary regressions, I employ the two-way FE model across different samples to reveal potential heterogeneity in the previously obtained results.

a. Employment Status

The initial test of heterogeneity focuses on the employment status of the baseline group used to assess the influence of public work participation. In my primary estimations, I compared observations where individuals were engaged in public work with those observations where they were not involved. However, the non-public worker group of observations comprises two distinct subgroups with significant heterogeneity: observations where individuals are employed and those where they are unemployed. Differentiating between employment and unemployment is crucial when examining the impact of public work on individuals' health. Consequently, I employ the two-way FE model to estimate the effects within the subsamples of employed and unemployed individuals. It is important to emphasize that, by using a model with individual FE, the comparisons are conducted within the same individual. In essence, I am comparing the average change to the mean in the healthcare outcomes when the employment status changes between employed/unemployed and public worker, within each individual.

Table 4 reveals that the previous lack of significance in both inpatient care and drug prescriptions was attributed to the comparison between public work and employment observations. However, when focusing solely on the comparison between public work and unemployment, the results exhibit statistical and economic significance for all the considered outcomes.

Comparing public employment and unemployment observations, being a public worker is associated with an average reduction of around 1.36 monthly visits to the doctor. This coefficient is statistically significant at the 0.1% level and corresponds to a decrease of over 30% in outpatient care utilization compared to the average of the baseline group (unemployed individuals living outside beneficiary districts). Considering inpatient care utilization, public work observations demonstrate a reduction of 2.9 days spent in the hospital, representing a decrease of approximately 37% compared to the average days spent by the baseline group. This coefficient is also statistically significant at the 0.1% level. Regarding monthly prescriptions, the improvement is slightly smaller, with an average decrease of approximately 0.2 prescribed drugs. This decrease corresponds to a reduction of only 6% compared to the baseline group. Comparing public employment and employment provides substantially different results. Only outpatient care shows statistically significant coefficients, which are smaller than those for the unemployed subgroup. Public work reduces monthly doctor visits by 0.12 on average, a 4.9% decrease compared to the baseline group.

These results show that engaging in public work significantly improves the health of unemployed individuals without producing negative health effects compared to regular employment.

b. Men and Women

Another relevant heterogenous test concerns the difference between the impact of public work among men and women. Given the elementary and manual/physical work that most public workers perform, there is a chance that the health of men and women are differently affected. Importantly, the representativeness of women and men in public work is almost identical in the dataset (Table A.7).

The results are presented in Table 5 - Heterogeneity Test: Men and WomenTable 5. The coefficients of public work participation for every health outcome differ among these two groups, although only in outpatient care they are statistically significant. While for men, participating in public work leads, on average, to a reduction of approximately 0.11 visits to the doctor (compared to its mean, within each individual and year), to women that value is of approximately - 0.18. These values represent a reduction of 4.7% and 7%, respectively, when compared to the average visits of their respective baseline groups.

The interaction coefficients between PWP participation and residence in a beneficiary district are equally insignificant at the 5% level across all regressions when run separately for women and men. In any case, living in a district with a lower development index changes the relationship between public work and the health outcome considered.

c. Age Cohort

Following the same thought process of the comparison between men and women, it is also interesting to observe whether the effect of public work participation varies at different age groups. For the sake of simplicity, I divided my sample into two groups, young and old, based on the median value of the age distribution. Observations with an age lower than 40 years-old are considered young, while those with an age equal or above 40 years-old are classified as old. As in the men/women distribution, young and old observations have a similar distribution in terms of public work presence (Table A.8). Table 6 shows differences across all outcomes, with statistically significant results in both outpatient care and drugs prescription.

Concerning outpatient care, participation in the PWP has a stronger impact on the sample of individuals above 40 years-old, with an average reduction of approximately 0.16 visits per month compared to the mean, where and when an individual is observed in public work. In the subgroup of young individuals, this reduction is of approximately 0.12 visits per month. The coefficients are statistically significant at the 1% level, and their values represent a decrease of approximately 6.4% and 4.7% in the monthly visits to the doctor, respectively.

When it comes to monthly drugs prescribed, the coefficients of the different subgroups have opposite signs. While in the young group, PWP participation leads to an average decrease of approximately 0.05 monthly prescriptions, in individuals above 40 years-old the monthly prescriptions increase approximately 0.04. Despite being statistically significant at the 5% and 1% level, respectively, these coefficients do not represent an economically significant result. Young individuals have a decrease of approximately 2% compared to their baseline group, while to the observations in the old group the increase is of approximately 1.6%.

d. Budapest

The final heterogenous test in my study focuses on differentiating observations based on their residence in or outside of Budapest. This distinction is particularly relevant due to the significant socioeconomic and demographic role that Budapest plays in the context of Hungary (Brown, Greskovits, and Kulcsár 2007).

Excluding Budapest from the sample does not significantly alter the results, as shown in Table 7. The coefficient for public work participation on outpatient care is -0.1764 in the regression without Budapest, compared to -0.1586 when including Budapest. The coefficients for inpatient care and prescribed drugs regressions are not statistically significant at any level. Conversely, when running the regression solely for the Budapest districts, the coefficient for outpatient care is not significantly different from 0 at any level, while the coefficient for drugs prescribed is significant at the 5% level. However, it lacks economic significance, with an average increase of 3.45% in monthly prescribed drugs compared to the baseline mean.

Table 4 - Heterogeneity Test: Employment Status

	Outpatient Care Full Sample	Outpatient Care Unemployed	Outpatient Care Employed	Inpatient Care Full Sample	Inpatient Care Unemployed	Inpatient Care Employed	Drugs Prescribed Full Sample	Drugs Prescribed Unemployed	Drugs Prescribed Employed
Public Work	-0.1586*** (0.0160)	-1.3650*** (0.0947)	-0.1218*** (0.0151)	-0.1380 (0.1506)	-2.9006*** (0.5985)	0.1811 (0.1551)	0.01175 (0.0155)	-0.2053*** (0.0568)	0.01861 (0.0156)
Beneficiary District	-0.08489*** (0.0119)	-0.05445 (0.0743)	-0.07639*** (0.0118)	-0.05282 (0.0909)	0.4550 (0.3396)	-0.07108 (0.1017)	-0.02296^{+} (0.0122)	-0.2155** (0.0794)	-0.02387^{+} (0.0123)
Public Work x Beneficiary District	0.02919 (0.0185)	0.06139 (0.1154)	0.01642 (0.0178)	-0.007997 (0.1885)	1.3769* (0.6131)	-0.1913 (0.1960)	0.04131* (0.0198)	0.07204 (0.0700)	0.03847^{+} (0.0199)
Constant	4.9841*** (0.1497)	6.0338*** (1.7019)	4.7579*** (0.1473)	4.8121*** (1.0942)	7.5221* (3.1883)	4.8023*** (1.1387)	6.6414*** (0.1414)	4.0981*** (0.7530)	6.5392*** (0.1414)
N	21343061	1488382	20617172	1013315	156604	838053	29283850	1948858	28724284
R^2	0.2039	0.4546	0.1925	0.5224	0.6178	0.5283	0.3304	0.4851	0.3314
Baseline Mean	2.556536	4.451854	2.491444	5.203126	7.90831	4.858394	2.921463	3.511633	2.911276

Notes: Clustered robust standard errors (in parentheses); $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard Errors are clustered at the district level; All regressions have individual and year FE; Explanatory variables and controls are lagged 1 month; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section. Each regression was run on different subgroups: unemployed regressions considered public work and unemployed observations; employed regressions considered public work and employed observations.

Table 5 - Heterogeneity Test: Men and Women

	Outpatient Care Full Sample	Outpatient Care Men	Outpatient Care Women	Inpatient Care Full Sample	Inpatient Care Men	Inpatient Care Women	Drugs Prescribed Full Sample	Drugs Prescribed Men	Drugs Prescribed Women
Public Work	-0.1586*** (0.0160)	-0.1163*** (0.0186)	-0.1849*** (0.0198)	-0.1380 (0.1506)	-0.4289 (0.3493)	-0.001496 (0.1732)	0.01175 (0.0155)	-0.01899 (0.0230)	0.03037 (0.0190)
Beneficiary District	-0.08489*** (0.0119)	-0.01474 (0.0162)	-0.1209*** (0.0142)	-0.05282 (0.0909)	0.2036 (0.2326)	-0.08378 (0.0943)	-0.02296^{+} (0.0122)	-0.01978 (0.0163)	-0.02910^{+} (0.0164)
Public Work x Beneficiary District	0.02919 (0.0185)	0.007770 (0.0236)	0.03767^{+} (0.0223)	-0.007997 (0.1885)	0.4787 (0.4071)	-0.2597 (0.2155)	0.04131* (0.0198)	0.05175^{+} (0.0301)	0.03674 (0.0238)
Constant	4.9841*** (0.1497)	5.5897*** (0.2038)	4.5606*** (0.1550)	4.8121*** (1.0942)	10.915*** (2.2224)	3.5980** (1.2098)	6.6414*** (0.1414)	6.2861*** (0.1588)	6.8968*** (0.1751)
N	21343061	7666438	13676623	1013315	321885	691430	29283850	12613217	16670633
R^2	0.2039	0.2478	0.1781	0.5224	0.5632	0.4901	0.3304	0.3671	0.3059
Baseline Mean	2.556536	2.449452	2.615134	5.203126	5.9628	4.872444	2.921463	2.954584	2.89677

Notes: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Robust standard errors, in parentheses, are clustered at the district level (198 clusters); All regressions include individual and year FE; Explanatory variables and controls are lagged 1 month; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section. Each regression was run on different subgroups: men regressions considered only men observations; women regressions considered only women observations.

Table 6 - Heterogeneity Test: Age Cohort

	Outpatient Care Full Sample	Outpatient Care Young	Outpatient Care Old	Inpatient Care Full Sample	Inpatient Care Young	Inpatient Care Old	Drugs Prescribed Full Sample	Drugs Prescribed Young	Drugs Prescribed Old
Public Work	-0.1586*** (0.0160)	-0.1258*** (0.0234)	-0.1648*** (0.0200)	-0.1380 (0.1506)	-0.3310 (0.2412)	0.1111 (0.2382)	0.01175 (0.0155)	-0.05060* (0.0241)	0.04989** (0.0189)
Beneficiary District	-0.08489*** (0.0119)	-0.1318*** (0.0128)	-0.006670 (0.0195)	-0.05282 (0.0909)	-0.03985 (0.1019)	-0.02467 (0.1984)	-0.02296^{+} (0.0122)	-0.007842 (0.0140)	-0.04183* (0.0170)
Public Work x Beneficiary District	0.02919 (0.0185)	0.0003251 (0.0266)	0.03483 (0.0240)	-0.007997 (0.1885)	0.1530 (0.2783)	-0.1497 (0.2970)	0.04131* (0.0198)	0.05383^{+} (0.0280)	0.02917 (0.0263)
Constant	4.9841*** (0.1497)	2.0590*** (0.1508)	6.4808*** (0.2670)	4.8121*** (1.0942)	3.9752* (1.5540)	6.1349** (2.1914)	6.6414*** (0.1414)	4.7759*** (0.1570)	7.0306*** (0.2158)
N	21343061	8339937	12926566	1013315	402673	588885	29283850	8784191	20423668
R^2	0.2039	0.2492	0.1941	0.5224	0.5507	0.5090	0.3304	0.2781	0.3490
Baseline Mean	2.556536	2.547544	2.566678	5.203126	4.771504	5.604034	2.921463	2.532068	3.094846

Notes: Clustered robust standard errors (in parentheses); $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard Errors are clustered at the district level; All regressions have individual and year FE; Explanatory variables and controls are lagged 1 month; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section. Each regression was run on different subgroups: young regressions considered only observations under 40 years-old; old regressions considered only observations equal or greater than 40 years-old.

Table 7 - Heterogeneity Test: Budapest

	Outpatient Care Full Sample	Outpatient Care No Budapest	Outpatient Care Budapest	Inpatient Care Full Sample	Inpatient Care No Budapest	Inpatient Care Budapest	Drugs Prescribed Full Sample	Drugs Prescribed No Budapest	Drugs Prescribed Budapest
Public Work	-0.1586***	-0.1764***	-0.06490	-0.1380	-0.1246	-0.2708	0.01175	-0.0005394	0.1032*
	(0.0160)	(0.0163)	(0.0405)	(0.1506)	(0.1581)	(0.4779)	(0.0155)	(0.0162)	(0.0471)
Beneficiary District	-0.08489***	-0.08128***		-0.05282	-0.04254		-0.02296^{+}	-0.02969*	
	(0.0119)	(0.0136)		(0.0909)	(0.1060)		(0.0122)	(0.0145)	
Public Work x Beneficiary District	0.02919	0.04373*		-0.007997	-0.02384		0.04131*	0.05459**	
	(0.0185)	(0.0186)		(0.1885)	(0.1945)		(0.0198)	(0.0202)	
Constant	4.9841***	4.8587***	5.5136***	4.8121***	4.7549***	4.8887	6.6414***	6.3877***	7.9946***
	(0.1497)	(0.1743)	(0.2269)	(1.0942)	(1.1571)	(3.4724)	(0.1414)	(0.1530)	(0.2471)
N	21343061	17583035	3747162	1013315	859688	148865	29283850	25028816	4241441
R^2	0.2039	0.1963	0.2483	0.5224	0.5135	0.5731	0.3304	0.3389	0.2889
Baseline Mean	2.556536	2.534234	2.620224	5.203126	5.195912	5.280578	2.921463	2.90329	2.983564

Notes: Clustered robust standard errors (in parentheses); $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard Errors are clustered at the district level; All regressions have individual and year FE; Explanatory variables and controls are lagged 1 month; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section. Each regression was run on different subgroups: No Budapest regressions excluded observations from Budapest districts; Budapest regressions considered only observations from Budapest districts.

IX. Conclusion

I have estimated the impact of participating in public work in Hungary on individuals' health. I use the Admin3 Database from the KRTK and exploit the fact that after September 2011 participation in public work is identifiable. This coincides with the time where heavy reforms were introduced in the Hungarian Public Work Program, with a huge increase in investment and individuals enrolled, what enriches the dataset concerning public work participation.

When running a pooled OLS model, the impact of the program on the considered outcomes is statistically significant, despite the modest size of the coefficients. These results do not significantly change when adding Year and District FE. However, when introducing individual FE, accounting for time-invariant individual characteristics that might confound this relationship, the results drastically change. Concerning outpatient care, the coefficients are still statistically significant, but lose any economic significant. Participating in public work leads individuals to use outpatient care, on average, approximately less 0.16 times per month. Concerning inpatient care and drugs prescribed, they are statistically insignificant both statistically and economically. I test for heterogeneity and find significant different results among groups. The positive impact of public work on monthly outpatient care is bigger for women and old people than for men and young individuals. The results are also driven by the districts outside Budapest, with the coefficient for the districts in Budapest being statistically insignificant.

When testing for heterogeneity on the employment status, I find that public work has positive and statistically significant effects on every outcome considered. Particularly, participating in the program leads to a significant reduction of inpatient and outpatient care when compared to unemployment, and it does not significantly differ from participating in the primary labour market. Enrolment in the Hungarian PWP leads to a 30% decrease in outpatient care and a 37% decrease in inpatient care compared to the averages of unemployed individuals residing in non-beneficiary districts. On average, this translates to approximately 1.36 fewer monthly visits to the doctor and nearly 3 fewer days spent in the hospital.

Various specifications, incorporating time-invariant individual and district characteristics and time-specific variation common among individuals, coupled with the comprehensive dataset, offer strong support for these findings. However, further research should examine the robustness of these results by testing them under new specifications and econometric techniques. Additionally, future studies could consider the multiple reforms implemented in the program since 2011, variations in spatial implementation, and individual differences in the starting period and duration of the program participation.

Another caveat in my research stems from my inability to differentiate the underlying reasons for outpatient and inpatient care and the specific drugs prescribed. The nature of the job performed may conceal distinct patterns across various health dimensions (e.g., physical and mental health) within the obtained results. Nevertheless, the KRTK contains a dataset with detailed inpatient and outpatient care information, with access to the International Classification of Diseases (ICD) codes. The same dataset includes detailed information on the prescriptions, containing the different Anatomical Therapeutic Chemical (ATC) codes. Future research should leverage this dataset's availability to unravel potential disparities in the impact of public work on various healthcare outcomes. Moreover, an upcoming version of the linked administrative data "Admin" is currently being prepared, covering more recent years, presenting an exciting opportunity to expand the research with newer observations.

X. Policy Recommendations

In light of the positive health effects observed when comparing public work participation to unemployment, there is a compelling case for expanding the program's coverage by easing certain enrolment conditions. This expansion could effectively a larger number of unemployed individuals to benefit from the program and improve their well-being. Moreover, these finds are a great opportunity to address the stigma and discrimination associated with participating in the Public Work Program, where public awareness and demystification on the program can be raised through campaigns and public debate. Additionally, they create an opportunity for the adoption and reinforcement of public work programs in other countries.

However, one should not overlook critical aspects of the workfare reform. First and foremost, it is crucial to recognize that public works represent only one facet of the broader landscape of Active Labour Market Policies. The considerable investment in the Hungarian Public Work Program has come at the expense of other policies (Vidra, 2008). Therefore, conducting a comprehensive policy assessment to determine the program's efficiency and effectiveness needs research into alternative scenarios and their potential outcomes.

Secondly, while the absence of significant differences in health outcomes between engaging in public work and regular employment is an encouraging finding, it is essential to interpret the results of this research in the appropriate context. The Hungarian Public Work Program, as the flagship of the workfare shift in the country, has been accompanied by substantial cuts to social assistance programs, resulting in the deterioration of living conditions for the most vulnerable segments of Hungarian society (Vidra, 2008; Duman & Scharle, 2011). Consequently, the positive health effects observed may reflect the broader consequences of a weakened welfare state model. Therefore, I recommend striking a careful balance between expanding public work coverage and providing adequate social assistance to those unable to access the program.

Thirdly, while the health of individuals is a primary concern, the program should incorporate it within its highest goal of re-employment of unemployed individuals, equipping them with the necessary skills to secure decent jobs in the primary labour market. Proper reforming of the program entails a shift in its conceptualization from a mere employer of cheap and unskilled labour to a trainer that equips participants with relevant skills. The implementation of these changes could be effectively accomplished through collaboration with private employers (e.g., expanding incentives for hiring individuals enrolled in the program and allowing private employers to host public works).

Nevertheless, it is relevant to emphasize that further research is imperative before any concrete policy decisions can be made. Additional studies are needed to deepen our understanding of the program's long-term impacts, potential unintended consequences, and the most effective approaches to implement and evaluate similar initiatives in diverse socio-economic contexts.

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Appendices

Table A.1 - Descriptive Statistics: Public Work and Dependent Variables

Variable	Observations	Mean	Median	Standard Deviation	Min	Max
Months of Public Work	5,830,88	36.99166	37	19.20133	1	76
Outpatient Care (Times)	36,336,912	2.547178	2	2.767794	1	108
Inpatient Care (Times))	2,813,154	5.941264	3	7.153132	.5	31
Prescriptions (Number)	48,748,456	3.283827	2	3.532693	1	274

Table A.2 - Descriptive Statistics Within Employment Status: Control Variables

Group	Variable	Observations	Mean	Standard Deviation	Min	Max
Public Work	Income Days	5,734,962	29.14611	4.153346	0	31
	Wage Month	5,734,962	76727.85	17645.02	-132000	2952993
	Working Hours	5,723,088	39.31018	3.010216	1	80
	Child Transfer	5,830,887	1.231071	11.21707	0	125
	Pension Transfer	5,830,887	3.080705	24.8957	0	214
	Unemployment/ Sick Transfer	5,830,887	25.67477	95.16333	0	706
	Other Transfers	5,830,887	5.23875	51.05409	0	531
Employed	Income Days	123,418,302	29.34298	4.696918	0	31
	Wage Month	123,418,302	213569.7	317516.8	1	8.01e+08
	Working Hours	107,976,962	37.79122	6.586775	1	99
	Child Transfer	123,418,302	2.442737	15.67559	0	125
	Pension Transfer	123,418,302	6.209962	35.00754	0	231
	Unemployment/ Sick Transfer	123,418,302	9.584633	60.64216	0	707
	Other Transfers	123,418,302	5.227795	50.99305	0	531
Unemployed	Income Days	2,432,582	.0019037	.2408989	0	31
	Wage Month	2,432,582	-595.8891	33041.29	-6800000	0
	Working Hours	1,522,377	37.44315	6.889597	1	93
	Child Transfer	77,304,447	10.14125	30.76634	0	125
	Pension Transfer	77,304,447	22.69223	64.06666	0	231
	Unemployment/ Sick Transfer	77,304,447	12.81463	65.33561	0	706
	Other Transfers	77,304,447	26.57078	112.466	0	531

Table A.3 - Descriptive Statistics within Employment Status: Dependent Variables

Group	Variable	Observations	Mean	Standard Deviation	Min	Max
Public Work	Outpatient Care (Times)	925,342	2.364923	2.512199	1	65
	Inpatient Care (Times)	68,924	5.031426	5.894115	.5	31
	Prescriptions (Number)	1,571,338	3.510781	3.969507	0	138
Employed	Outpatient Care (Times)	22,650,741	2.444095	2.589552	1	108
	Inpatient Care (Times)	1,210,243	4.201352	4.994857	.5	31
	Prescriptions (Number)	31,340,129	2.912444	2.998353	0	274
Unemployed	Outpatient Care (Times)	12,760,829	2.743369	3.064924	1	84
	Inpatient Care (Times)	1,533,987	7.354853	8.256326	.5	31
	Prescriptions (Number)	15,837,020	3.996236	4.274953	0	197

Table A.4 - Outpatient Care: Lags Specifications

	Outpatient Care No Lag	Outpatient Care 1 month lag	Outpatient Care 3 months lag	Outpatient Care 6 months lag	Outpatient Care 1 year lag
Public Work	-0.1707*** (0.0156)	-0.1586*** (0.0160)	-0.1317*** (0.0171)	-0.1224*** (0.0166)	-0.09298*** (0.0148)
Beneficiary District	-0.07934*** (0.0118)	-0.08489*** (0.0119)	-0.06986*** (0.0138)	-0.05430*** (0.0130)	-0.01540 (0.0151)
Public Work x Beneficiary District	0.05922** (0.0192)	0.02919 (0.0185)	0.007285 (0.0202)	0.002272 (0.0185)	-0.006129 (0.0188)
Constant	6.4822*** (0.1572)	4.9841*** (0.1497)	4.1729*** (0.1542)	4.2357*** (0.1601)	4.5045*** (0.1654)
N	21574840	21343061	20770952	19863704	17997982
R^2	0.2207	0.2039	0.1963	0.1979	0.2042
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Clustered robust standard errors (in parentheses); $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard Errors are clustered at the district level; All regressions have individual and year FE; All regressions have as dependent variable the number of times an individual used outpatient care in the given month; Explanatory variables and controls are lagged according to each regression; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section.

Table A.5 - Inpatient Care: Lags Specifications

	Inpatient Care No Lag	Inpatient Care 1 month lag	Inpatient Care 3 months lag	Inpatient Care 6 months lag	Inpatient Care 1 year lag
Public Work	-0.3191 (0.1979)	-0.1380 (0.1506)	0.2296 (0.1663)	-0.04358 (0.1671)	-0.2299 (0.2915)
Beneficiary District	-0.04962 (0.1022)	-0.05282 (0.0909)	0.08075 (0.0994)	-0.02812 (0.1236)	0.1251 (0.1545)
Public Work x Beneficiary District	0.2589 (0.2322)	-0.007997 (0.1885)	-0.4022+ (0.2188)	-0.1692 (0.2308)	-0.02986 (0.3225)
Constant	10.746*** (1.1308)	4.8121*** (1.0942)	2.1422+ (1.1093)	1.2285 (1.1947)	-2.3049+ (1.3034)
N	942538	1013315	1007918	963053	870008
R^2	0.5370	0.5224	0.5264	0.5321	0.5407
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Clustered robust standard errors (in parentheses); $^{+} p < 0.10$, $^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$; Standard Errors are clustered at the district level; All regressions have individual and year FE; All regressions have as dependent variable the number of times an individual used outpatient care in the given month; Explanatory variables and controls are lagged according to each regression; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section.

Table A.6 - Drugs Prescribed: Lags Specifications

	Drugs Prescribed No Lag	Drugs Prescribed 1 month lag	Drugs Prescribed 3 months lag	Drugs Prescribed 6 months lag	Drugs Prescribed 1 year lag
Public Work	-0.005555 (0.0145)	0.01175 (0.0155)	0.02962^{+} (0.0161)	0.05548^{***} (0.0152)	0.07903^{***} (0.0174)
Beneficiary District	-0.01810 (0.0119)	-0.02296^{+} (0.0122)	-0.01308 (0.0124)	-0.01472 (0.0128)	0.002297 (0.0136)
Public Work x Beneficiary District	0.04148^{*} (0.0185)	0.04131^{*} (0.0198)	0.03926^{+} (0.0206)	0.02910 (0.0205)	0.02111 (0.0224)
Constant	7.1414^{***} (0.1446)	6.6414^{***} (0.1414)	6.6262^{***} (0.1376)	6.1907^{***} (0.1264)	6.3953^{***} (0.1333)
N	29604263	29283850	28514184	27332626	25003328
R^2	0.3315	0.3304	0.3322	0.3365	0.3447
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: Clustered robust standard errors (in parentheses); $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Standard Errors are clustered at the district level; All regressions have individual and year FE; All regressions have as dependent variable the number of times an individual used outpatient care in the given month; Explanatory variables and controls are lagged according to each regression; Public Work is a dummy variable equal to 1 if the individual was a public worker in the given month, 0 otherwise. Beneficiary District is a dummy variable equal to 1 if the individual was living in a beneficiary district, 0 otherwise. All regressions include the full set of control variables, estimates of which are not reported here. Detailed characterization of each variable and set of controls in the data section.

Table A.7 - Public Work Observations: Men and Women

Group	Public Work	Frequency	Percentage
Men	Yes	3,046,427	2.94
	No	100,574,101	97.06
	Total	103,620,528	100.00
Women	Yes	2,784,460	2.71
	No	100,148,648	97.29
	Total	102,933,108	100.00

Table A.8 - Public Work Observations: Age Cohort

Group	Public Work	Frequency	Percentage
Young	Yes	2,620,091	2.50
	No	102,327,425	97.50
	Total	104,947,516	100.00
Old	Yes	3,210,796	3.16
	No	98,395,324	96.84
	Total	101,606,120	100.00