Disinformation Spread and Targeting Politicians on Czech Twitter

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Abstract

Previous research on the use of fake Twitter accounts shows that right-wing trolls appear more frequently than left-wing trolls. Also, right-wing politicians are more likely to benefit from troll activity. Trolls serve as amplifiers of political messages, they are also employed to intimidate other users, that includes activists, journalist, or politicians. While there is evidence that trolls operate on Czech Twitter, their behaviour had not been studied. This papers aims to analyse whether troll activity depends and the sentiment of the targeting message on politician's ideology. Data on Twitter troll activity towards Czech politicians were collected and analysed using statistical models. The results show right-wing trolls are more likely to target right-ting politicians. The sentiment of the messages also increases the more the politician's ideology to the right, however, the relationship between politician's ideology and message sentiment is not significant.

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Contents

1 Introduction

How is the political disinformation spread on social media in Czechia? Why are politicians targeted by trolls? The rise of social media platforms enabled sharing large amount of information both by real people or anonymous accounts. While information can travel fast in real-time, it may be unverified and originated from dubious source. In their study of EU Parliamentary Elections 2019, Marchal et al. (2019) show that 4% of the content circulating on social media in pre-election period came from fake news websites. Studying the same Elections, Silva and Proksch (2021) find right-wing parties were more likely to benefit from employment of trolls and bots on Twitter during the pre-election period. There is evidence that also domestic political actors use political trolling to change narrative around unpopular bills (Zhdanova and Orlova, 2018) or to discredit opposition (Gorwa, 2017). Further, Gorwa (2017) finds that the case of Poland there is twice as much right-wing than left-wing Twitter bot accounts. Trolls can be employed to target public personas with disinformation and using trolls and bots can even lead to death threats (Aro, 2020), or increased harassment and hate speech (Tucker et al., 2018). For example, a well-respected Czech journalist left Twitter due to frequent troll attacks (Zelenka, 2022). Lewis and Marwick (2017) also explains, proliferation of right-wing disinformation and trolling aims to control public debate and focus it around right-wing policies and creating general notion of public support for such policies. Additionally, Borra et al. (2017) finds that both left-wing and right-wing Dutch politicians are targeted by trolls, the right-wing politicians are mentioned more positively than the left-wing politicians. Further, studies by Karatas and Saka (2017), Simchon et al. (2020) show the trolls communicate with highly polarised language. Karatas and Saka (2017) conclude the Turkish Twitter space has been overtaken by trolls who set the agenda for discussion. This often means discrediting opposition and promotion of government policies (Karatas and Saka, 2017). In general, troll activity may both damage reputation of public personas, it may also lead to detriment of public debate.

Reports that analysed Czech fake news websites content show their articles targeted mostly opposition parties in pre-election period, mainly the left-wing Pirates party and the right-wing coalition SPOLU (TOGETHER) (Čeští elfové, 2021, Šefčíková, 2022, Threats). While the disinformation diffusion outside social media seems to be well mapped, the effort to map disinformation on Twitter has been limited to short reports of investigative journalist on disinformation community of Twitter accounts (Šlerka, 2021), or Zelenka (2022)'s investigative on four popular Czech Twitter accounts which engaged in trolling activity. While Zelenka (2022)'s sample was small and contained only four cases, he reported that the real life persons behind operating these accounts were related to various Czech political parties. For example, one of the troll accounts was traced to be a PR advisor to the Chairwoman of the Chamber of Deputies. In addition, Míková (2021) finds that eleven troll accounts comment under tweets of the most followed Czech political accounts, nonetheless, she merely studies whether trolls activity exists in relation to political accounts without providing further detail on what could be the trolls motivation to target Czech politicians. While there is evidence of trolling activity on Czech Twitter, their strategies remain unclear. What could explain politician trolling on Twitter in the context of Czech Republic? This paper seeks to test whether ideology-related targeting strategies are employed by Czech trolls as the cases from other countries show. That is, whether the amount of political trolling and the sentiment of trolling messages depends in the ideology of the politician. As reported by Silva and Proksch (2021), Gorwa (2017), Fichman and McClelland (2021) in the case of the European Elections, Poland, and the US, it expected to find that right-wing politicians are targeted more by trolls. Additionally, the right-wing trolls target right-wing politicians with positive messages as in case the (Borra et al., 2017) study on Dutch Twitter trolls. While ideology may not be the only factor that explains troll behaviour on Twitter, trolls also may be used as tool of international hybrid warfare (Aro, 2016) or can be part of political campaigning strategies (Keller et al., 2020), this paper examines what whether ideology of politicians motivates frequency of political trolling and the sentiment of the troll message.

In the first part of the paper, a brief literature review on the current state of online disinformation research will be presented. Second, theory and mechanism behind political trolling will be introduced. Third, data collection, methods, and analyses will be described in the research design section. The paper ends with discussion section where limitations and other possible explanations for political trolling are presented.

2 Literature Review

2.1 (Political) Disinformation

Disinformation has been widely studied throughout disciplines of social sciences. Each study, however, may define disinformation differently depending on the research objectives. For the purpose of this work, the (Tucker et al., 2018) broad definition of disinformation also used by Guess and Lyons (2020) will be used: intentional spread false or inaccurate information. Other than disinformation - an information meant to deceive, this also includes fake news (junk news), online propaganda (spread of information promoting one candidate or party), or hyperpartisan news (Tucker et al., 2018) - highly partisan media outlets that resemble mainstream media (Faris et al., 2017). This paper is also concerned with specific type of misleading information - political disinformation. Such type of deception targets discourse concerning political issues (Hwang, 2020) or political issues (Tucker et al., 2018).

2.2 Disinformation Diffusion

In the context of social media, disinformation may be promoted as links to web page articles that take the user out of the platform and lead them to fake news or hyperpartisan outlet (Tucker et al., 2018). While the individual user may click on the post, they may engage in liking, or sharing the content with deceptive information. Other than links, the users may directly share posts about their preferred topic - either by directly sharing their thoughts, or re-sharing other users' posts, the post may also include pictures, photos, memes, or videos. While this describes individual user behaviour on social platforms, the origin of disinformation spreading on such platform are usually not random users from general population. The efforts to spread disinformation are often coordinated and diffused by specialised groups of accounts such as bots, trolls, (Woolley and Howard, 2018) fake-news sites, politicians or governments (Tucker et al., 2018). Current research shows there are several potential ways through which to produce and disseminate disinformation on social media (Tucker et al., 2018). These strategies might be employed, for example, by international actors to influence domestic politics (Aro, 2020), by politicians or political parties as campaign tool (Gorwa, 2017, Zhdanova and Orlova, 2018), or they might be used by governments to intimidate activists, journalist, or their opponents (Keller et al., 2020, Monaco and Nyss, 2018, Saka, 2018, Karatas and Saka, 2017)

2.2.1 Bots

Bots are accounts created by a software that produce human-like activity on social media. Bots may generate text messages on their timelines or respond with to other accounts' conversations. In general, the goal is to mimic human-like activity in larger volumes and in repetition (Woolley and Howard, 2018). That means, once a group of bots coordinates their activity, for example, by repeatedly posting messages about a topic or a hashtag, it looks as though the users of the social media network engage in a conversation. Hence, the conversation becomes salient due to bot accounts responses, re-sharing, and posting which leads to popularising any topic in question (Shao et al., 2018). In order to do this, the bot accounts coordinate their actions in so called clusters – a dense network of bot accounts that cooperates when sharing and posting messages (Hindman and Barash, 2018). This strategy is efficient as individual bots may not rely on large number of followers. It is sufficient for them to coordinate when they post messages and the social media algorithm promotes the posts they share. Especially in the case of Twitter, the topics re-shared and promoted by bots reach real users who continue to share the disinformation message and amplify the reach of bot-diffused messages (Shao et al., 2018, Vosoughi et al., 2018). For example, Hindman and Barash (2018) find that most of the disinformation in their 2016 US Presidential Election sample of Twitter data is shared by bots or semi-automated accounts. Hindman and Barash (2018) obtained 10 million tweets from period before and after the Elections. They linked 700,000 accounts to 600 fake news or conspiracy websites. By using machine learning models, they finds that about 33% of accounts of their 100 most followed accounts were identified as bots. Their analysis shows the network of the rest of the accounts in the had been densely connected. These accounts re-shared tweets with links leading to fake news websites with their activity culminating on the election evening.

Another strategy employed by bots is to target users with bigger influence and larger number of followers to proliferate their messages (Shao et al., 2018, Stella et al., 2018). That means, if a popular account has many followers and bots respond to their conversations, more people can notice the message. Further, bots may be used as a tool to artificially increase number of followers of an account (Niederer and Groen, 2020). By increasing number of followers, the account becomes more popular which increases the reach of messages they proliferate. In general, bots are useful tool to increase reach of an account or topic. Recent paper that analysed proportions of automated accounts among followers of selected Czech politicians shows that about 20% of Andrej Babiš's, who is a former Czech PM, Twitter account is followed by bots (Málek, 2019).

The disinformation proliferation on social media is an interconnected and overlapping system. Different actors may use both trolls, bots, or semi-automated accounts to proliferate their message. Common strategy of how to employ both bot or troll accounts is astroturfing - a coordinated disinformation campaign by which fake accounts seek to evoke narrative around an issue – for example, positive or negative view about a politician or a policy (Keller et al., 2020). Keller et al. (2020) investigated the Twitter activity in the 2012 South Korean presidential election where the where the National

Intelligence Service (NIS) coordinated fake accounts activity to support their preferred candidate. While Keller et al. (2020) concludes that the coordinated activity seemed to have little impact on public opinion and Tucker et al. (2018) call for more research into impact of online disinformation campaigns on offline political behaviour, there is indication astroturfing still may be useful tool in disinformation spread. As Labzina (2017) finds, organised astroturfing by Russian trolls helped to push Russian narrative into Wikipedia articles where it has a potential to reach wide audience.

2.2.2 Trolls

Other effective strategy how to disseminate disinformation on social media is to use trolls. Trolls are accounts operated by real people (Hindman and Barash, 2018) that publish such content that seeks to spark an emotional reaction in other users, for example, by offending other users, sharing distressing or shocking images (Lewis and Marwick, 2017). While some troll accounts may operate solemnly for personal reasons and individual gain, there is a large proportion of trolls who are paid for their troll-like activities (Tucker et al., 2018). One of the most well-known examples is the Russian ”troll-factory” - the Internet Research Agency (IRA). The IRA hired trolls sought to influence the political discourse on Twitter by sharing conspiracy content (Bastos and Farkas, 2019). As Aro (2016) describes, trolling may also be used on international level. The IRA trolls may target not only politicians and try to influence election, trolls can also target public figures which publicly oppose Russian influence (Aro, 2020). Aro herself, as journalist investigating on the IRA agency, became also target of trolls. Disinformation about her persona circulated both on fake news websites and on social media where she frequently received death threads, harassment, and mockery (Aro, 2020). As Aro (2020) writes in her book which maps Russian trolls activities, similar reputation-damaging and harassment scenarios were also applied to target public figures in Serbia, Lithuania, or the UK.

Political trolling has been also present in other countries as a tool of domestic politics to silence opposing voices (Monaco and Nyss, 2018). Monaco and Nyss (2018) describe how a campaign to discredit a former Ecuadorian congresswoman Martha Roldó first started in state newspaper, however, continued as harassment in form of abusive messages on Twitter. Saka (2018) finds that the Turkish government used trolls during 2014 anti-government protests. Further, Karatas and Saka (2017) study concludes Turkish government-supported trolls use polarising language and their activity converted the Turkish Twitter space into highly polarised environment. The interviews with experts on the Polish disinformation scene suggest that trolling-like activities aim to molest political activists on social media (Marchal et al., 2019). Gorwa (2017) and Jankowicz (2020) also find that the disinformation is not only spread by foreign agents on Polish social media, Polish trolls hired by domestic political powers also employ disinformation diffusion strategy by frequently posting comments under messages of other users (Gorwa, 2017). Gorwa (2017) further finds that fake accounts coordinate their activity on Facebook to promote desired opinions. Such political campaigns are run on Facebook by an anonymous company paid by political parties. As mentioned earlier, a Czech journalist reported on connection between four Czech popular Twitter accounts and politicians from various political parties (Zelenka, 2022). Former PM Andrej Babiš reportedly met with the real person who is responsible for running of the troll accounts during one of his party events and maintains connection with owner via WhatsApp (Zelenka, 2022). Recently his Twitter account shared a disinformation imagine that targeted an investigative journalist that uncovered his role in Pandora papers (Zelenka, 2022). Further, it has been reveled that another popular Twitter account sometimes engaged in tense conversations, occasionally even using hard language, belonged to people who are members of the currently governing parties, or worked for the government (Zelenka, 2022). In his article, Zelenka (2022) describes that the accounts owners identity was openly known among selected journalist, however, their identities were unknown to other Twitter users and the general public. All four accounts, however, were connected to different parties. While Zelenka (2022) brings similar evidence of troll activity on Czech Twitter similar to Míková (2021), it is not clear whether trolling-like activities on Czech Twitter are targeted against politicians themselves, and if they are, which politicians are targeted more frequently than other and if there are differences across political spectra.

Míková (2021) sought to identify if Czech politicians are targeted by bots, trolls, and automated accounts on Twitter. While she finds that there has been at 11 troll-like accounts that commented on tweets of Czech politicians, she examines only a sample of 10 most followed political accounts on Czech Twitter. That also means, she includes accounts who are not politicians but are politically active. For example, the account of the Czech president press secretary. In summary, she merely shows that troll accounts, which as described below, operate on Czech Twitter and in relation to Czech politicians, however, it still remains unclear whether bots and trolls targeting activity is related to political ideology in case of Czechia. In other words, both Zelenka (2022) and Míková (2021) show there is a presence of trolls, nonetheless, their strategies of targeting remain investigated. This is problematic, as trolls and bots are able to skew the debate on social media to their topic of preference and creating different picture of non-troll users think (Keller et al., 2020).

2.2.3 Politicians

Political representation itself may be implicated in sharing dubious content on their social media (Tucker et al., 2018). Politicians may engage in such activity to gain popularity (Lewis and Marwick, 2017). As Lewis and Marwick (2017) describe, Donald Trump used his social media to disseminate various conspiracy theories and disinformation. His Twitter account served as amplifier for disinformation content, such as that Barack Obama was not born in the US. They may also employ spreading disinformation as type of populist discourse which may lead to group polarisation (Hameleers, 2020). Hameleers (2020) in his qualitative study of Trump's and Wilder's speeches shows both of these politicians play a key role in spreading populist disinformation. They employ the disinformation narrative by frequently attacking mainstream media and elites as corrupt and dishonest (Hameleers, 2020). Journalists found that during the Dutch 2017 general elections fake Twitter accounts were used to popularise message of various political parties and also discredit their opponents (Borra et al., 2017). Humprecht (2019) analysed the stories on two prominent fact-checking websites in Germany and the US. Using mixed-method she finds that in the English-speaking countries the fact-checking websites are more concerned with analysis of political accounts than in German-speaking countries. By comparing the frequency with which German and US politicians where fact-checked on the websites, she finds that German-speaking politicians are fact-checked less. She explains this is because German-speaking politicians share less likely to publish false claims and also because the fact-checkers websites in German-speaking countries contain less fact-checked content in relation to politicians. As Baum et al. (2017) describes, the links may not only be shared by politicians - the social bots may coordinate their activity to either send or target politicians with the alternative media links. While politicians may not share disinformation links as often as bots or trolls, usually high number of their followers reads what they post (Baum et al., 2017). This means, the political representation may not engage in sharing dubious content often, however, once they do, the marginalised message receives spotlight which would not receive without the politicians' help. In the case of Czech Republic, reports show that politicians across Czech political spectra appear as authors or interviewees on Czech fake news websites (Švec, 2021, Čeští elfové, 2021). At the same, another left-wing party, KSČM (the Czech Communist Party), shares disinformation on their official website under "alternative sources" tab (Chudomelová et al., 2017).

2.3 Ideology

Other than pushing topics to go viral by coordination of retweets, activity on popular accounts and artificially increasing number of followers, bots and trolls maybe also be used to target and harass other accounts. In general, far-right groups are more likely to engage in disinformation dissemination (Lewis and Marwick, 2017, Baum et al., 2017). Gorwa (2017) finds that the proliferation of bots on the Polish side of Twitter is mainly disseminated by right-wing. However, he also describes a case where both left-wing and right-wing trolls engaged in an ”online fight” by reporting each other and suspend the opponents social media page. Fichman and McClelland (2021) find that in the US, Republican politicians are more likely to be targets of trolls that the Democrats and that female politicians are more likely to be targeted than their male counterparts. Similarly, Borra et al. (2017) finds that right-wing politicians are more likely to be mentioned by trolls positively than the left-wing politicians. Additionally, Borra et al. (2017) develops a step-by-step guide on how to identify political trolling on Twitter. First, they identify two key topics that were widely discussed one month prior to the election and they scrap all tweets concerning both topics. Second, they count how many times each of the users who tweeted on the topic mentioned a politician and take the accounts that mentioned more than 100 times. Third, they conduct qualitative analysis of the tweets. Fourth, they visualise the proportion of positive or negative mentions from the accounts. They find the left-wing politicians were target the most with negative mentions.

In the case of Turkey, the right-wing trolls Twitter were used to promote government policies Saka (2018), Karatas and Saka (2017) that lead to high polarisation of this social media website (Bulut and Yörük, 2017). As Lewis and Marwick (2017) the reason behind disinformation spread by right-wing groups is to shift the debate towards right-wing policies and crate a notion of desirability of such policies by public and politicians.

In the case of Czechia, there are reports that the Czech left-wing Pirates party was attacked the most by disinformation prior to the Parliamentary 2021 elections (Čeští elfové, 2021). Further, the right-wing coalition SPOLU (TOGETHER) was attacked by pro-Russian Sputnik news (Šefčíková, 2022). Yet, as previously mentioned, parties of the coalition SPOLU (TOGETHER) and ANO party leader Andrej Babiš are related to the most popular Czech Twitter accounts which engage in trolling activities (Zelenka, 2022). In other words, these four troll accounts are owned by people who communicate or work with politicians of the respective parties (Zelenka, 2022). Based on the previously mentioned Zelenka (2022)'s investigative, there is some indication right-wing trolls might be operating on Czech Twitter, yet, it is not documented who these troll target - whether they target fellow right-wing politicians as in the case of the US (Fichman and McClelland, 2021) and the Netherlands (Borra et al., 2017). Similarly, both right-wing and left-wing parties were attacked by disinformation outside social media on fake news website. In other words, it remains unclear whether trolls on Twitter could follow the same targeting strategies as the fake news sites and target left-wing parties, or to seek overtake the narrative and target more right-wing politicians.

3 Theory

3.1 Why Are the Members of Parliament Themselves Targeted by Twitter Trolls?

Following what has been mentioned above, ideology might play role in spreading disinformation, as far-right groups and parties are more likely to engage in such practice to increase the the popularity of their views (Lewis and Marwick, 2017). Other factors such as troll attacks used as a tool of international hybrid warfare or political campaigning by opposition or government before the elections, nonetheless, the ideology will be examined as central factor that influences political trolling on Czech Twitter in this paper.

3.1.1 Ideology

Analysing the US presidential election 2016 on Twitter, Hindman and Barash (2018) find that both right and left wing accounts spread disinformation. Similarly to Hindman and Barash (2018), Golovchenko et al. (2018) looked the troll activity during these elections. He also finds Twitter trolls both from left or right may engage in trolling and disinformation diffusion. Additionally, Gorwa (2017) reports that the left and right-wing trolls may also fights each other. For example, left-wing Facebook trolls managed to report an opposing right-wing Facebook site with such frequency, that Facebook eventually blocked the right-wing page. Gorwa (2017) also finds that both right-wing and left-wing trolls operate on Polish Twitter, however, the right-wing troll appear twice more in his sample of Twitter accounts. As Lewis and Marwick (2017) describes, sharing fake news and engaging in online trolling activities became main domain of the right-wing groups, especially, of several diverse far-right groups with each promoting their own cause such as anti-LGBT or anti-feminist views. Analysing the Dutch Twitter space in pre-election period, Borra et al. (2017) found to be the case that left-wing parties are more likely to be attacked by trolls, while right-wing politicians tend to be mentioned positively by troll accounts. Lewis and Marwick (2017) main explanation for such disinformation tendencies to appear mainly on the right-wing spectra is that the right-wing groups seek control of public discourse. Lewis and Marwick (2017) explain that is because the far right-groups perceive-left as a winning culture and seek to overturn the mainstream narrative right-wing ideas. As Gorwa (2017) describes, not only far-right groups but also mainstream right-wing parties may use online space and social media to influence online discussions. Their hired trolls' strategy includes targeting opinion leaders and popular accounts with their comments and coordinate such activity to create the notion of a public's relation selected issues and policies.

Further, Silva and Proksch (2021) find evidence that far-right parties are more likely to benefit from malicious content being spread on Twitter and that far-right parties were followed significantly more by fake accounts than left-wing accounts. The reason behind artificially increasing followers' base on Twitter is to make the followed accounts more popular and increase the reach of their posts (Tucker et al., 2018). Based on the above, the reason behind employing trolls to mention politicians or comment under politicians posts is to create a notion of agreement with the politician statement or to show support for the politician themselves (Woolley and Howard, 2018). As previously described, fake accounts on Twitter, whether trolls and bots, tend to coordinate their activity to increase reach of their message or the popularity of the politician. Hence, trolls could target politicians positively when they seek to support the politician and promote their ideas or policies (Woolley and Howard, 2018). This will lead to general notion of politician's policy acceptance by other users on Twitter, it may also lead to promotion of such policies as the Twitter algorithm would promote tweets or users who receive large amount of likes, or responses on their posts.

Since Silva and Proksch (2021), Lewis and Marwick (2017), Borra et al. (2017), Gorwa (2017) find right-wing parties tend to benefit or are targeted positively by social media trolls and Zelenka (2022) finds three Czech trolls that display behaviour affiliated with Czech right-wing parties, the expectations for troll behaviour on Czech Twitter would also be that the trolls target more right-wing politicians, in order to promote right-wing ideas and increase the popularity of politician. Since such behaviour would aim to support the politician, also the sentiment of the trolling messages would be expected to be positive towards right-wing politicians. Similar scenario would also apply to the left-wing trolls. That is, when trolls would seek to support left-wing politicians, they could comment frequently and positively under their posts. In case a troll would promote right-wing ideas and message positively about right-wing politicians, it would be expected that they comments negatively under left-wing politicians posts. As documented by Karatas and Saka (2017), employing such tactics detriments public discourse and may lead to polarisation at least in the inline space.

H1: Whether politicians faces increased activity of political trolling depends on their party ideology. The more right on the political scale, the more likely are politicians being targeted by trolls and disinformation.

H2: The troll mentions are more likely to be favourable towards right-wing politicians.

4 Research Design and Analysis

4.1 Data

4.1.1 (DV) Targets of Political Trolling

To obtain measure of the which politicians and how much are exposed to political trolling, first, the list of troll accounts was created. The trolls for the list were taken from four sources, which will be explained below. In total, the list contains 70 accounts (see Appendix A). Based on the list, the troll accounts, the trolls Twitter timeline activity was obtained using Twitter API and Tweepy library for Python (Roesslein, 2020). The permissions to use official Twitter API were obtained by applying for Twitter Developer account - Academic Research track, as this track provides various methods of authentication for obtaining Twitter activity. Additional features that contain information about trolls were obtained - the number of followers, published tweets, date of account creation, and whether the account is protected or verified. These features were joined separately to the trolls list as the information was obtained using different method due to different Twitter authentication requirements. Second, list of politicians who were elected as MP either in the last elections in October 2021 or previous elections October 2017 was created. That is 321 politicians in total from which 219 has Twitter account (see Appendix B.1). The troll account responses were matched to political accounts to obtain frequency of how many times were politicians on Twitter targeted by these troll accounts. The process will be explained below.

4.1.2 Troll Accounts List

The list of troll accounts was compounded from four resources. Míková (2021) identifies 11 troll accounts operating under 10 most popular Czech Twitter accounts belonging to a politician. After scraping the last 400 tweets of these popular politicians accounts and their responses, using sentiment analysis she filters for only responses with negative sentiment and for accounts which responded more than three times to a conversation or twice for various conversations. Then, she manually analysed the tweet responses and removed angry users, users who responded often but in respectful manner, and accounts whose responses were coherent and logical despite using swear words and rude language. She identifies 8 accounts which tweet responses regularly, contain abusive language and insults, try to provoke interaction, and their tweets seem to be nonsensical. That means, for example, troll might only use emojis, photos, links, or slurs to reply. She identifies other 3 accounts who may be trolls. Such accounts display the same behaviour as the mentioned troll category, however, they also target other users in their communication and it is unclear weather the accounts are interconnected with other accounts. Since both categories show similar behaviour in regards to conversations under political accounts which follows the definition of troll (responses regularly, contain abusive language and insults, try to provoke interaction) all 11 accounts will be considered for the analysis. Example of such troll behaviour is shown in Figure 1 (1). The current Czech MP, and former Minster of Commerce and Minister of Transport, Karel Havlíček shares a tweet criticising current government bill that aims to decrease inflation. The troll account @CapekCapekJiri responds: ”Go away you servile Bureš muck!”. By Bureš, the troll refers to the alleged undercover name of the former PM Andrej Babiš who was given such a name as an alleged agent StB (the secret police of the communist Czechoslovakia before 1989).

Figure 1: Example of troll responses under the current Czech MP, Karel Havlíček

Second, as mentioned earlier, Zelenka (2022) writes about four anonymous popular accounts on Twitter who often comment on political events and under political accounts. Similar to Míková (2021) definition of troll, they respond regularly to conversation of others and they sometimes contain abusive language and insults. From trolls identified by Míková (2021) they differ by popularity and having thousands of followers. Since these accounts are popular, they also comment on non-political content and aim to provide entertainment to their followers. These accounts were also anonymous until April 2022 when Zelenka (2022) uncovered their identity and showed all four such accounts are related to some extent either to current opposition party ANO or the governing coalition SPOLU (TOGETHER). Below (2) there is an example of now a former Czech MP Mikuláš Peksa who engaged in a conversation under his own tweet. In his response, he says the politicians should be capable to tell even unpleasant truth to people. @VVetvicka responds: ”You are just a wretch full of problems. You are welcome, you don’t have to pay me for the truth, my service is for free.”

Figure 2: Example of troll response to Pirate’s MP at the time, Mikuláš Peksa

Third, another investigation of disinformation community on Czech Twitter by Šlerka (2021) showed 54% of these accounts recent tweets are responses to other conversations. Šlerka (2021) identifies 95 accounts who shared at least twice link to a website that published disinformation about Covid-19. At the time of Šlerka (2021)’s data collection the Twitter accounts were engaging in spreading Covid-19 disinformation. During his work Šlerka (2021) placed accounts included in his analysis to a Twitter public list of accounts. That means, the activity of all users in the list may be viewed in one place. Scrolling through both Šlerka (2021)’s lists of opinion leaders and users who spread disinformation, their recent activity displayed in the list shows they also frequently tweet about Russian aggression in Ukraine. The main goal of Šlerka (2021) investigation was to identify the most influential disinformation accounts. To do that, he uses so called affinity index - a measure that seeks to show how influential is one account within a target group it tries to reach. The measure compares the number of followers of an account, the number of followers from the target group it tries to reach and the total number of Czech Twitter users. He finds 14 accounts that show high affinity which indicates they are the opinion leaders in the group. While the main goal of his analysis was to identify influential accounts, Šlerka (2021) finds, the sample of 95 accounts who shares disinformation and consists both of anonymous and real users, other than responding to each other, also respond to politicians. The politician who responded the most was the former Minister of Health, Adam Vojtěch, and the former PM, Andrej Babiš. While Šlerka (2021) does not investigate further the nature of the responses to politicians these accounts make, looking at their activity using the previously mentioned Šlerka (2021)'s lists, their activity suggests they engage in trolling of political accounts. The example in Figure 3 (3) shows how one these accounts comments under Czech MP Twitter post criticising the lack of willingness to cut Russia from SWIFT at the beginning of the war. @janka402 briefly responds:"Idiot...you are a real idiot."

Figure 3: Example of troll-like response by disinformation account to a former MP, Miroslav Kalousek

However, the accounts from Šlerka (2021)'s sample seem to engage in such trolling like activities with less frequency than troll account's from Míková (2021)'s and Zelenka (2022)'s lists. For example, the rest of activity on @janka402 accounts shows the accounts responds to variety of politicians, most with dubious content and frequently with links to other websites, blogs, or posts which contain factually dubious content. Further, not all 95 accounts from Šlerka (2021) will be used for the analysis as Šlerka (2021) has not released the whole dataset of his analysis (mainly omitting accounts which shared less than 5 links to disinformation sites). He identifies 14 accounts as opinion leaders giving their high affinity index and additional 26 accounts who shared more than 5 links to a disinformation site related to Covid-19. These accounts will be used as Šlerka (2021) findings suggest, these account are the most active. One opinion leader account out of Šlerka (2021)' list of 40 will be removed, as this account belongs to a politician Lubomír Volný. He was placed on the list mainly due to disinformation spreading on his Twitter account and high affinity index. However, he was also an MP during 2017 - 2021 and appears on the list of politicians.

Fourth, Czech think-thank European Values developed a list of 52 disinformation websites actively operating in Czechia. They identify disinformation website based on two general criteria: the website's editorial policy does not include the journalism ethics and standards, their ownership structure and financing of the web is unclear, and the content they share either includes proven disinformation or publishes personal opinions as facts. The website must publish more than five articles per month and have on average more than 2000 visits per month (Krátka Špalková et al., 2021). From their list, 15 of such websites also have a Twitter account. While three of them seem to be only automatic bots with almost no engagement, only serving to occasionally post links to fake news articles, at least another three seem to be engaging in conversation with politicians. The example below (4) shows an opposition MP at the time, Ivan Bartoš, tweeting about the Pirates' party fight against corruption, debt, and inflation. The response of @RealitaDne ("Day Reality"):"You for sure, you disgusting junkie".

4.1.3 Politicians List

The Czech Parliament consists of 200 MPs. In order to obtain list of politicians who own a Twitter account, both MPs before and after October 2021 elections were considered as a potential target of trolls (see Appendix B.1). Using Python's library BeautifulSoup,

Figure 4: Example of troll-like response by disinformation website account to an opposition MP at the time, Ivan Bartoš

the both lists of MPs elected in 2017 and 2021 were obtained by scraping the Czech Statistical Office website. For 321 MPs in total, it was manually checked that 219 MPs owned a Twitter account. Their Twitter account names were then run through Twitter API using Tweepy library to obtain their Twitter account ID, number of followers, and date of creating of their account. This list contains both politicians who resigned and those who replaced them during the term.

4.1.4 Ideology of Politician

To determine how Czech political parties and their member stand on the political scale 2019 Chapel Hill expert survey was used. The survey rates main Czech political parties on left-right scale from 0-10 where 0-Extreme left, 5-Center, 10-Extreme right. (Seth et al., 2020). During 2017 - 2021 election cycle, there were 8 MPs who changed their political affiliation out of which six own a Twitter account. Only one account of these was reelected in 2021 elections, therefore, the ideology of politician's new party is used. The other five politicians joined or established minor parties which are not part of the 2019 Chapel Hill measure. Therefore, the party affiliation from their 2017 election candidacy list will be used.

The 2019 Chapel Hill expert survey also provides a measure of party position towards the EU. The measure is based on the party stance towards European integration 2019 and takes values on scale 0-7; 1-Strongly opposed, 4-Neutral, 7-Strongly in favor (Seth et al., 2020).

4.1.5 Control Variables

There are other factors which could make a troll to be active under political accounts. For example, when a political account is popular, the message they tweet can have wide reach and can be more likely to circulate on social media. For that reason, the accounts that target politicians could focus on popular accounts. In order to account for targeting by popularity, the number of followers each political account has will be used. Still, this measure contains only how many followers each account had at the time of data collection and it does not account for any popularity changes over the time.

Similarly, Another factor that could contribute to decisions what political accounts to target could be number of tweets they post. While it might be the case that the political account does not belong to the most popular ones, the user might publish Tweets frequently, hence becoming a target rather than a politician who appears on Twitter occasionally unnoticed by trolls.

Another factor that could contribute to decisions what political accounts to target could be the popularity of a tweet itself. The tweet popularity is a sum of likes, responses, quotes, and retweets the tweet received. While it might be the case that the political account does not belong to the most popular ones, the user might publish a tweet that receives many likes and retweets. As a consequence, this can boost the tweet to become popular on the network and potentially attractive for distribution dubious messages or harassment. All the measures - number of followers, number of tweets by politician, and popularity of political tweet - were scraped in two stages using Twitter API. The process of obtaining followers count and number of tweets is described above in the Politicians list subsection, while the information about political tweet were obtained while scraping tweets of politicians which is explained below.

4.1.6 Troll Ideology

The ideology of the troll included list was manually checked. The trolls were split into two groups - left or right - based on their latest (about 30 tweets to the past) activity on their Twitter account timeline. Based on Lewis and Marwick (2017) list of far-right groups commonly shared content, accounts that shared anti-LGBT, anti-feminist, conspiracy post were coded as right. Similarly, accounts who either publicly stated their disagreement with left-wing parties or policies were coded as right wing. In contrast, accounts that endorsed left-wing policies or explicitly manifested support for LGBT were coded as left-wing.

4.1.7 Matching Troll Activity to Political Accounts

All timeline activity of a troll user going back to 3,200 tweets was obtained using the Twitter API and Tweepy library for Python (Roesslein, 2020). The advantage of scraping Twitter timelines is that the process is more time efficient, however, allows going back only 3,200 tweets of activity to the past for one account and some of the troll accounts tweeted with such frequency that this limit was exceeded. In order to obtain timeline activity for such accounts, different approach was used - using Twitter API directly without the Tweepy library and with a different authentication method. All 70 troll accounts from the list were inputted for scraping and 37 returned results. Out of the 33 which were not scraped, 5 was either locked (inaccessible by other users or those who want to scrap information about the account) or suspended by Twitter. The rest of the accounts (28) were not scrapped due to mismatch of troll IDs in the trolls list and the actual troll account ids discovered in the late phase of the project. The mismatch was created due to automatic change by Excel of the last number of integer longer than 15 digits (helenclu). That means, the troll author ID number's last 4 digits automatically change to 0. These changes are automatic and random both in excel and csv formats. In total, 170,064 tweets of troll activity were obtained between 1st May 2021 and 13th May 2022, out of which 9,340 mentioned a political account from the list 219 politicians who have Twitter. 102 politicians by targeted at least once by troll.

The troll timeline activity includes users' original tweets and also retweets, quoted tweets, shared urls, or media, and responses to other conversation. The scraped troll accounts tweets were filtered for responses to conversations and to mentions on their timeline. For example, if a troll account posted in a conversation under political account, such response is recorded as one mention of a political account. At the same response tweet, more politicians can be mentioned. However, this usually happens if the troll account response to a politicians who retweets or quotes another political account (see example below 5). Therefore, the second, third, or fourth mention made by troll can be a mention that does not target the political account in question, such mentions are only recorded as a part of the response to the political account which created the tweet. That means, such additional mentions do not appear due to troll targeting but due to Twitter API settings. The example below shows a response from troll @Mengele85170837 to Karel Havlíček, who is now an opposition MP from ANO party. While the first mention clearly indicates the troll responds to the politician who posted the original tweet, it also shows a second mention belongs to another politician Andrej Babiš who is mentioned, however, is not the author of the tweet.

Figure 5: Example of various mentions by troll where only the first one responds to political tweet author

For that reason, when a troll posts under a political conversation, the political account who is mentioned first is considered as a targeted. Further, those tweets produced by trolls which are not responses to conversation can still target political accounts. For example, when a troll accounts tweets for their followers and mentions political account. To capture such activity, the data were filtered for tweets which are not responses, nonetheless, contain political account mentions. In this case, all mentions were considered. In contrast, if the troll account retweeted or quoted content of a politician, such mentions through retweet are omitted. The reason for not using the retweets and quotes where politician was not mentioned, it means the account who quoted or retweeted did not intend comment on the politician with intention to get a response. In other words, when a retweet or a quote is made, it appears on the troll timeline reaching mainly troll's followers. While the troll may comment negatively or positively on the political tweet, the politician or other users outside troll's network may not even notice of such troll activity. Finally, The troll activity dataset contains information about who these accounts mentioned and the ID of the conversation it was responded to. Then, the dataset of 219 political accounts was matched with troll account activity.

One of the potential pitfalls of such matching is the Twitter blocking function. This function enables Twitters users to block activity of other accounts on towards their account. This means, when a user decides to block another user, the block account cannot see, nor respond, or mention the other account. While the answers or mentions still remain publicly on display, the blocking functions limit any future interaction between the users. For instance, one could still see tweets posted by troll accounts under a political account in a conversation. However, when the troll account is blocked by the politician, the troll account can no longer respond or mention them. The example below shows a troll activity towards two politicians - Petr Fiala and Petr Gazdík. The troll themselves mentioned that they have been blocked by both politicians, therefore, there are no more mentions for Petr Gazdík after 4th April 2022 and no mentions of Petr Fiala after 5th May 2022 (see figure below 6).

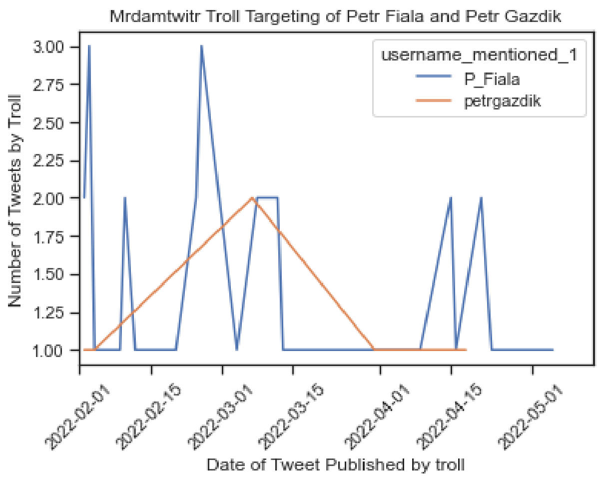

Figure 6: Petr Gazdik and Petr Fiala targeted by twitter troll Mrdamtwitr

4.1.8 Matching Troll Activity to Information about Political Accounts

The 9,340 troll tweets which targeted political accounts were matched with data containing information about the account and the tweet they targeted. First, the troll-produced messages where matched with political accounts activity using the conversation IDs. That is, when a tweet is published by a politician, it receives a unique ID - conversation ID. If troll responds to politician's tweet, their reply will contain exactly this conversation ID recorder with the their troll message. In order to obtain the political activity to which was possible to respond, 91,587 of political tweets were scraped using both timeline scrap method and the method that scraps historical data and uses different authentication method.

In order to create the dataset with 9,340 tweets and information from 91,587 political tweets they could have targeted, three joins were performed. First, the troll account could be responding to the politician directly under their post, hence, such troll response was joined using the previously mentioned conversation ID and to avoid duplication, the username of the political account targeted was added to the joining keys as well. However, the troll dataset also contained direct mention of politician troll original tweets. These responses were added to the response dataset leaving the information about political tweet empty. Additionally, there were also mentions which were responses to a political tweet, however, the tweet had been deleted. For that reason, conversation ID of political tweet did not exist and the could not be joined with troll targeting tweet. After joining the features of political tweets, the information about political accounts - the number of followers, tweets and when the political account was created - were joined to the troll replies dataset.

4.1.9 (DV) Sentiment of Troll Activity

The 9,340 troll texts that targeted political accounts with direct mentions or replies to political conversation were analysed using python's Sentiment Vader which is part of the NLTK library (Hutto and Gilbert, 2014). The Tweets were first translated to English using API connected to the Google Translator. To avoid loosing texts which contained only emojis (e.g. smilies, or vomiting emojis) that are analysed as object that carry sentiment value, emojis were first separated and then joined with the English text.

The reason for translation is that the Sentiment Vader library runs on English lexicon that rates words with different sentiment values. However, the NLTK library does not include lexicon in Czech language, therefore, the text were translated to English (see Appendix 7). However, as the troll activity is not always translatable, for example, by using slur words or compounds of Czech words that are meant to offend, the English lexicon was enriched by sentiment scores for these typical Czech swear words and other frequently used words that could not be translated but carried a sentiment value. The words for additional sentiment scoring were selected by manually analysing 3,000 rows out of 9,340 rows of translated text. For example, often used word which is not a slur but carries negative connotations is "Anofert". It means to say that the ANO party is part of Andrej Babiš formerly owned Agrofert. Since Vader lexicon rates words between -4.0 to 4.0 (negative to positive where 0 us neutral) (Ma, 2020), words like Anofert were coded as -1.0, whereas other more serious slurs were coded as more negative. Applying the extended lexicon to the sentiment analysis, 274 tweets moved to negative sentiment category (see Appendix 8).

4.2 Analysis

First, the dataset was aggregated to the politician-troll level. That means, each of 219 politicians on the list was matched with 37 trolls, and the count of how many time the troll targeted politician was obtained. However, this aggregation turned to be problematic as the ideology measure from 2019 Chapel Hill expert dataset was obtained on a party level. Hence, the ideology observations were repeated which violated the regression assumption of independent observations. The solution for the issue could be ideological scaling per politician using models which analyse text such as (Huang, 2017), however, due to the limited time, this method could not be used. Therefore, the dataset was aggregated to politician level. That means, for each politician the number of times they were targeted by right wing troll, left wing troll, and was the sentiment of the messages posted by right wing and left wing trolls. The measures for number of followers and tweets per politician were used in log version (see Appendix for comparison D). The models were run using Python's open source module Statsmodels (Seabold and Perktold, 2010).

4.2.1 Dependent Variable - Frequency of Targeting

The dependent variable - frequency of politician being targeted by right-wing troll - followed the Poission distribution. Hence, the Posisson regression model for discrete counts was run first. However, the check for overdispersion showed values much larger than 0, 21.29. That means, it is more suitable to use negative binomial model. Since the sample contained 124 observation with zero on the dependent variable, that is, 124 politicians were not targeted by right-wing troll, the check whether to use zero inflated negative binomial model was conducted. Using definition of zero inflated sample check by (Lüdecke et al., 2021), first, the negative binomial model was fitted to the whole dataset and then run again to make prediction for the dependent variable. All predictions with value <0.8 were considered as zeros. In total, the model predicted 103 zeros which is less than the observed 124 zeros. By (Lüdecke et al., 2021) definition, the model should be, therefore, considered zero inflated as the amount of 0 predicted was lower than the amount of 0 observed and the model underfitted zeros. While Python's module Statsmodels offers option of applying negative binomial model with inflated zeros, the implementation turned to be timely inefficient as the elementary set up of the formula entering the model allows only one independent variable input without controls. Two-step approach was applied instead (Hendershot).

First, binomial model was run on a newly created variable *targeted* with 0 for when politician was not targeted by right-wing troll and 1 for when the politician was targeted. While in the first step the control variable for political tweet popularity could not be used due to loss of observations, using only cases were politicians were targeted in the second model, this control was applied. Additionally, in regards to (Analytics) recommended checks, the OLS (see Appendix for results table (F.1) and residuals (15)) and simple negative binomial models were run (see Appendix for results table (F.2) and and residuals (16)).

The first binomial model reports positive relationship between being targeted by right-wing troll - original values of ideology range between 0-10, where 0 - extreme left, 10 - extreme right.

Dep. Variable:	target	**No. Observations:**	219
Model:	GLM	**Df Residuals:**	214
Model Family:	Binomial	**Df Model:**	4
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-86.732
Date:	Tue, 07 Jun 2022	**Deviance:**	173.46
Time:	18:30:25	**Pearson chi2:**	166.
No. Iterations:	10	**Pseudo R-squ. (CS):**	0.4382
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-6.1767	1.076	-5.740	0.000	-8.286	-4.068
Political Ideology	0.1950	0.110	1.777	0.076	-0.020	0.410
Sum Tweets Left Trolls	1.0004	0.318	3.149	0.002	0.378	1.623
Politician Followers Log	0.1186	0.153	0.773	0.440	-0.182	0.419
Politician All Tweets Log	0.5953	0.172	3.461	0.001	0.258	0.932

Table 1: First Stage: Results of Binomial Regression

That is, the more to the right, more likely to be targeted by right-wing troll. The reported with for such relationship is p-value .076 (see Table 1 and Appendix for residuals plot 17). The second model (see Table 2 and Appendix for residuals plot 18) shows there is a significant positive relationship between the number of tweets produced by right wing troll and unit increase of ideology to the right with p-value .000. While the there is also positive relationship between right-wing and left-wing troll produced tweets with p-value .060 in the second model, the coefficient value for left-wing trolling tweets is low comparison to other coefficients.

Dep. Variable:	Sum Tweets Right Trolls	**No. Observations:**	95
Model:	GLM	**Df Residuals:**	89
Model Family:	NegativeBinomial	**Df Model:**	5
Link Function:	Log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-347.81
Date:	Tue, 07 Jun 2022	**Deviance:**	90.017
Time:	18:35:20	**Pearson chi2:**	138.
No. Iterations:	100	**Pseudo R-squ. (CS):**	0.7883
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-5.9330	0.777	-7.632	0.000	-7.457	-4.409
Political Ideology	0.2453	0.066	3.721	0.000	0.116	0.374
Sum Tweets Left Trolls	0.0045	0.002	1.883	0.060	-0.000	0.009
Politician Followers Log	0.8282	0.102	8.119	0.000	0.628	1.028
Politician All Tweets Log	0.1950	0.100	1.942	0.052	-0.002	0.392
Politician Tweet Popularity Log	-0.1760	0.058	-3.054	0.002	-0.289	-0.063

Table 2: Second Stage: Results of Negative Binomial Regression

4.2.2 Dependent Variable - Sentiment of Right-wing Troll Tweets

Since the sentiment variable followed normal distribution, OLS method was used. While the relationship between ideology and tweet sentiment is positive, the relationship is not significant with p-value .891 (see Table 3 and Appendix for residuals plot 19).

Dep. Variable:	Sentiment Right Trolls	**R-squared:**	0.085
Model:	OLS	**Adj. R-squared:**	0.044
Method:	Least Squares	**F-statistic:**	2.081
Date:	Tue, 07 Jun 2022	**Prob (F-statistic):**	0.0898
Time:	20:55:27	**Log-Likelihood:**	-8.7966
No. Observations:	95	**AIC:**	27.59
Df Residuals:	90	**BIC:**	40.36
Df Model:	4		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.4358	0.185	-2.357	0.021	-0.803	-0.069
Political Ideology	0.0023	0.017	0.138	0.891	-0.031	0.035
Politician Followers Log	-0.0174	0.026	-0.683	0.496	-0.068	0.033
Politician All Tweets Log	0.0573	0.025	2.279	0.025	0.007	0.107
Politician Tweet Popularity Log	0.0087	0.014	0.604	0.547	-0.020	0.037

Omnibus:	0.116	**Durbin-Watson:**	1.939
Prob(Omnibus):	0.944	**Jarque-Bera (JB):**	0.009
Skew:	0.024	**Prob(JB):**	0.995
Kurtosis:	2.999	**Cond. No.**	99.0

Table 3: Sentiment of Right Wing Trolls Messages Results

While the H1 was confirmed - the more to the right, the more mentions politician receives by right-wing trolls, the H2 was rejected - there is a positive relationship between ideology and the tweet sentiment being positive, however, this relationship is not significant.

For both dependent variables, the sentiment of targeting tweet and the frequency of targeting, the OLS and two step zero inflated negative binomial models were run on the desegregated data where assumption of observations independence violated were run (see Appendix E).

5 Discussion

Similarly to what Silva and Proksch (2021), Lewis and Marwick (2017), Borra et al. (2017), Gorwa (2017) describe, Czech right-wing politicians are more likely to be targeted by trolls, mainly right wing trolls. This could mean, also trolls on Czech Twitter target right-wing politicians more to increase popularity of their message or account. However, there are limitations to findings of this paper and will be discussed below.

5.1 Limitations

Both ideology measure for political account and troll accounts could be improved by using text-analysis tools. For example, using Wordfish (Huang, 2017) both political tweets and trolls tweets could be run in the model which would place each accounts' text on a scale. Therefore, the whole sample all of 9,340 observation in less aggregated level could be analysed without violation the assumption of observations independence. Similarly, both troll and political tweets topics could have been obtained to determine weather troll targeted politicians who mention specific topics.

The list of trolls could be extended not only by using Excel non-changed troll account IDs but using Borra et al. (2017) guide how to identify troll behaviour on Twitter. He develops a method how to identify troll behaviour from random sample of tweets per controversial topics. Therefore, the troll sample could be larger than 70 troll accounts. Additionally, this method could have been used regularly to obtain historical data on troll behaviour. For example, after the data collection for this paper finished, the troll account Mrdamtwitr was suspended. While the responses to political accounts by this account still exists when searching for the political tweet, looking at the account itself, all its activity became inaccessible. By obtaining months, even years of data, one would be able to track weather troll activity and motivations change before or after elections.

Additionally, combing both approaches - improving the sample of trolls collected and the measure of their ideology - could improve the proportion of right-wing and left-wing trolls in the sample. That is, to collect such sample that is independent from pre-determined list and using ideological-scaling based on troll's tweets.

Also, the sentiment score could be improved by extended the lexicon by all the words in the sample that had not been translated. A better translation method such as using DeepL API could be employed.

5.2 Future Research

In the case of Czechia, mainly two other explanations for why politicians would be targeted by trolls on Twitter offer offer themselves - international hybrid warfare, and pre-election campaigning.

Disinformation campaign originating from foreign actors seek to influence election outcomes which then may lead to destabilisation of democracies (Baum et al., 2017). Such concerns have been also raised by the Czech security services and the government, with special caution to the Russian disinformation campaign (Eberle and Daniel, 2019). Political trolling is also a tool of international hybrid warfare to discredit public personas and influence domestic politics by foreign actors. In line what Syrovátka and Šefčíková (2021) claim, targeting pro-EU politicians could mean the trolls are used as tool of hybrid warfare, Russian disinformation campaign, to attack pro-Western parties. Targeting West oriented, pro-European, pro-NATO parties that vary on political spectrum may suggests foreign political actors may be behind trolling and the goal of such activity would be to influence the elections. Therefore, future research could focus on the role pro-EU stance of politician or party plays in targeting politicians by trolls. As mentioned above, analysing text both of troll and politicians for topics they mention, the future research could focus on which topics attract trolls and of EU, NATO or mentions of other institutions inflate the frequency of targeting.

As mentioned before, using trolls to discredit opponents have been used by domestic political actors in the Netherlands (Borra et al., 2017) or Poland (Gorwa, 2017), or Ukraine (Zhdanova and Orlova, 2018). While Czechia was heading towards its parliamentary elections in October 2021, a group of volunteers that monitors circulation of disinformation in Czech online space, Czech Elves, reported increased targeting of the opposition parties with disinformation (Čeští elfové, 2021a,b). It may be the case that using trolls could be a tool of pre-election campaigning, as in the case of in the 2012 South Korean presidential election (Keller et al., 2020). After the US 2016 Presidential Election, activity of some of the Twitter accounts responsible for spreading disinformation decreased after the election (Hindman and Barash, 2018). Hence, using trolls merely as tool of political campaign prior to the elections with intend damage the rival parties with harassment or disinformation, would be observed less after the elections, as party spending on the campaign and effort to win over the opposing sides decreases once the elections are over. Therefore, future reach could investigate whether the trolling activity could have been motivated by the upcoming elections and used as tool of campaigning strategy.

6 Conclusion

Social media are platforms where spread of online disinformation can thrive. There are various means how to proliferate disinformation, nonetheless, this paper focuses on explaining the phenomena of political trolling on Czech Twitter. Previous investigative reports or initial studies showed the trolls are active and may even target Czech political accounts. However, the patters in troll behaviour were unclear. Previous findings of Silva and Proksch (2021), Gorwa (2017) indicate that right-wing parties receive more trolling activity than left-wing politicians. At the same time, the sentiment of the right-wing trolls toward right-wing politicians is more positive than towards left-wing politicians

(Borra et al., 2017). The reasons behind employing trolls in regards to ideology include not only promotion of right-wing ideas and policies but also changing the narrative of public debate for right-wing policies to look generally preferred and accepted by public (Lewis and Marwick, 2017) which may lead to polarisation at least on the social media platform (Karatas and Saka, 2017). Therefore, the paper aimed to analyse whether trolls may be motivated by ideology when targeting politicians and target more right-wing politicians and what is the sentiment of such messages.

The results show, on line with the hypothesis, that the more right-wing Czech politician is, they receive more mentions and responses to their tweets. While the more to the right on political scale, the sentiment grows positive, the relationship is not significant. In line what was found in other countries about troll behaviour on Twitter (Silva and Proksch, 2021, Lewis and Marwick, 2017, Borra et al., 2017, Gorwa, 2017), the results indicate also Czech trolls target right-wing politicians more to increase popularity of their message or the political account. However, there are limitations to the findings, such as imbalanced troll sample by ideology, aggregated level of the data, or translation to English required for sentiment analysis on Czech tweets. There are other explanations which might explain troll activity on Czech Twitter. This might employing trolls as tool for political campaign prior to the October 2021 parliamentary elections. Trolls could also be used by foreign actors as tool of international hybrid warfare. Further research is needed to explain whether these factors could play role in troll activity motivation towards Czech politicians.

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A Trolls List

	author_id	troll_account_name	active	type	source_type	nickname	author_id_corrected	troll_followers_count	verified	protected	created_at_account	account_name	troll_ideology_guess_bi
0	1244355713897508864	SpendlikRoman	Yes	Troll	MA_Thesis	SpendlikRoman	1244355713897508865	13	FALSE	FALSE	2020-03-29 20:08:23+00:00	SpendlikRoman	right
1	1292200127868919808	PalzerRadim	Yes	Troll	MA_Thesis	PalzerRadim	1292200127868919811	2	FALSE	FALSE	2020-08-08 20:45:05+00:00	PalzerRadim	unknown
2	716864926162284544	CapekCapekjiri	Yes	Troll	MA_Thesis	CapekCapekjiri	716864926162284544	16	FALSE	FALSE	2016-04-04 05:48:11+00:00	CapekCapekjiri	left
3	1374780112714014720	CtiradMasin	No (Aug 21)	Troll	MA_Thesis	CtiradMasin	1374780112714014724	1	FALSE	FALSE	2021-03-24 17:48:27+00:00	CtiradMasin	unknown
4	775939875199528960	JiriMart	Yes	Troll	MA_Thesis	JiriMart	775939875199528960	11	FALSE	FALSE	2016-09-14 06:10:57+00:00	JiriMart	unknown
5	1379500721368932352	pavel_krupicka	No (Jul 21)	Troll	MA_Thesis	pavel_krupicka	1379500721368932358	1	FALSE	FALSE	2021-04-06 18:27:10+00:00	pavel_krupicka	unknown
6	1325381632593891328	Isabell21525070	Yes	Troll	MA_Thesis	Isabell21525070	1325381632593891333	100	FALSE	FALSE	2020-11-08 10:16:36+00:00	Isabell21525070	unknown
7	762371339621634048	Garmix1	Yes	Troll/User	MA_Thesis	Garmix1	762371339621634048	2	FALSE	FALSE	2016-08-07 19:34:26+00:00	Garmix1	right
8	2537423236	Mrdamtwitr	Yes	Troll	MA_Thesis	Mrdamtwitr	2537423236	24	FALSE	FALSE	2014-05-09 17:15:51+00:00	Mrdamtwitr	right
9	1254037388952772608	RazyHea1	No (Jul 21)	Troll	MA_Thesis	RazyHea1	1254037388952772609	0	FALSE	FALSE	2020-04-25 13:20:09+00:00	RazyHea1	unknown
10	1320690212310274048	Mengele85170837	Yes	Troll	MA_Thesis	Mengele85170837	1320690212310274048	5	FALSE	FALSE	2020-10-26 11:34:36+00:00	Mengele85170837	unknown
11	1023039085	ZarkoRaptor	Yes	User	Newspaper Article - Investigative	ZarkoRaptor	1023039085	312	FALSE	FALSE	2012-12-19 22:37:00+00:00		unknown
12	1035999857134235648	Lukas Pollert	Yes	User	Investigative Jounalism	pollert11	1035999857134235649	10670	FALSE	FALSE	2018-09-01 21:16:28+00:00	Lukas Pollert	righ
13	894454156647333888	Konspiracni Praxe	Yes	User	Investigative Jounalism	Konspraxe	894454156647333888	1186	FALSE	FALSE	2017-08-07 07:04:23+00:00	Konspiracni Praxe	unknown
14	1226962731057795072	Petr Vittvar	Yes	User	Investigative Jounalism	IVittvar	1226962731057795072	1428	FALSE	TRUE	2020-02-10 20:15:04+00:00	Petr Vittvar	unknown
15	1239302803832668160	Kilgore Trout	Yes	User	Investigative Jounalism	JohnGal72674903	1239302803832668161	1791	FALSE	FALSE	2020-03-15 21:30:01+00:00	Kilgore Trout	right
16	1381475947036180480	Petr Unger	Locked	User	Investigative Jounalism	CzUnger	1381475947036180481	847	FALSE	TRUE	2021-04-12 05:15:38+00:00	Petr Unger	right
17	1387677025511657472	Irish terrier,Czech republic	Locked	User	Investigative Jounalism	tarot_dog	1387677025511657473	1242	FALSE	TRUE	2021-04-29 07:56:20+00:00	Irish terrier,Czech republic	unknown
18	1453704807110348800	Neomarxistická Svině	Yes	User	Investigative Jounalism	neo_svine	1453704807110348806	929	FALSE	FALSE	2021-10-28 12:47:13+00:00	Neomarxistická Svině	left
19	1484006172	Roman Maly	Yes	User	Investigative Jounalism	MatesRoman	1484006172	834	FALSE	TRUE	2013-06-05 04:16:49+00:00	Roman Maly	right
20	248865181	David Zahumenský	Yes	User	Investigative Jounalism	dzahumensky	248865181	1703	FALSE	FALSE	2011-02-07 21:57:07+00:00	David Zahumenský	unknown
21	2494141045	JITA Splítková□□□□ □□	Yes	User	Investigative Jounalism	VasagitaS	2494141045	3259	FALSE	FALSE	2014-05-14 12:26:19+00:00	JITA Splítková□□□□ □□	right
22	388565021	Tomas Nielsen	Yes	User	Investigative Jounalism	TomasNielsen1	388565021	4747	FALSE	FALSE	2011-10-10 23:41:22+00:00	Tomas Nielsen	right
23	815926165261221888	Ivana Melkusova	Yes	User	Investigative Jounalism	MelkusovaIvana	815926165261221890	2395	FALSE	FALSE	2017-01-02 14:22:11+00:00	Ivana Melkusova	right
24	939530238	Jana Bobošíková	Yes	User	Investigative Jounalism	Bobosikova	939530238	2675	FALSE	FALSE	2012-11-10 17:32:18+00:00	Jana Bobošíková	right
25	955041243188297728	Nedy	Yes	User	Investigative Jounalism	NedyNadija	955041243188297728	1551	FALSE	FALSE	2018-01-21 11:35:51+00:00	Nedy	left
26	1421847885193400320	Richard Siemko	Yes	User	Investigative Jounalism	RSiemko	1421847885193400321	258	FALSE	FALSE	2021-08-01 14:59:36+00:00	Richard Siemko	unknown
27	1408159709371289600	Linsee84	Yes	User	Investigative Jounalism	Linsee841	1408159709371289601	4	FALSE	FALSE	2021-06-24 20:26:59+00:00	Linsee84	unknown
28	1368541387235409920	Noční můra	Yes	User	Investigative Jounalism	Marakua111	1368541387235409923	20	FALSE	FALSE	2021-03-07 12:37:56+00:00	Noční můra	right
29	1358890652659044352	Btctsla	Yes	User	Investigative Jounalism	Btctsla1	1358890652659044362	12	FALSE	FALSE	2021-02-08 21:30:57+00:00	Btctsla	right
30	1349471658315304960	Sancho Panza□□□□□□□□□□□□	Yes	User	Investigative Jounalism	SanchoCascajo	1349471658315304961	115	FALSE	FALSE	2021-01-13 21:41:41+00:00	Sancho Panza□□□□□□□□□□□□	right
31	1340356128266477568	DE-PRESCRIBING PHARMACIST	Yes	User	Investigative Jounalism	Davidech17	1340356128266477571	58	FALSE	FALSE	2020-12-19 18:00:21+00:00	DE-PRESCRIBING PHARMACIST	right
32	1272397827931504640	Patrik Kučera	Yes	User	Investigative Jounalism	PatrikKuera6	1272397827931504641	8	FALSE	FALSE	2020-06-15 05:17:53+00:00	Patrik Kučera	unknown
33	1245329220085170176	Tomas	Yes	User	Investigative Jounalism	Tomas48147122	1245329220085170176	59	FALSE	FALSE	2020-04-01 12:36:49+00:00	Tomas	unknown
34	1228718045905985536	Jarda U	Yes	User	Investigative Jounalism	jarda_u	1228718045905985536	329	FALSE	FALSE	2020-02-15 16:30:06+00:00	Jarda U	right
35	1215286306953224192	Vítězslav Novotný	Yes	User	Investigative Jounalism	VtzslavNovotn1	1215286306953224192	629	FALSE	FALSE	2020-01-09 14:57:30+00:00	Vítězslav Novotný	right
36	997853855705681920	Michaela Pírková	Yes	User	Investigative Jounalism	MicaelaPirkova	997853855705681921	535	FALSE	FALSE	2018-05-19 14:57:53+00:00	Michaela Pírková	right
37	930746503701909504	Lubomír Volný - VOLNÝ blok	Yes	Politician	Investigative Jounalism	lubomir_volny	930746503701909504	6708	FALSE	FALSE	2017-11-15 10:37:13+00:00	Lubomír Volný - VOLNÝ blok	right
38	876547390827843584	Ivan	Yes	User	Investigative Jounalism	Ivan55744544	876547390827843584	284	FALSE	FALSE	2017-06-18 21:09:18+00:00	Ivan	unknown
39	859418324442152960	Iva Zikešová	Yes	User	Investigative Jounalism	ivazikii	859418324442152961	303	FALSE	FALSE	2017-05-02 14:44:30+00:00	Iva Zikešová	unknown
40	837577458404712448	Marie Švédová	Yes	User	Investigative Jounalism	MarieSvedova	837577458404712448	60	FALSE	FALSE	2017-03-03 08:16:42+00:00	Marie Švédová	right
41	834412088915349504	MA3X7	Yes	User	Investigative Jounalism	MA3X8	834412088915349504	287	FALSE	FALSE	2017-02-22 14:38:39+00:00	MA3X7	unknown
42	724167969585115136	Jana Hrušková	Yes	User	Investigative Jounalism	janka402	724167969585115136	117	FALSE	FALSE	2016-04-24 09:27:53+00:00	Jana Hrušková	right
43	4726367657	milada krajíčková	Yes	User	Investigative Jounalism	AmritaJa	4726367657	43	FALSE	FALSE	2016-01-06 16:47:09+00:00	milada krajíčková	unknown
44	3226345085	josch265	Yes	User	Investigative Jounalism	josch265	3226345085	82	FALSE	FALSE	2015-05-01 15:13:19+00:00	josch265	right
45	1719042619	Jan Kysel	Yes	User	Investigative Jounalism	JanKysel	1719042619	19	FALSE	FALSE	2013-09-01 13:17:17+00:00	Jan Kysel	unknown
46	1669281894	Kamil Papežík	Yes	User	Investigative Jounalism	KamilPapezik	1669281894	43	FALSE	FALSE	2013-08-14 02:42:55+00:00	Kamil Papežík	right
47	1384632433	Petr	Yes	User	Investigative Jounalism	Petr99041589	1384632433	9	FALSE	FALSE	2013-04-27 14:39:44+00:00	Petr	unknown
48	566368379	Vasil Zelenák	Yes	User	Investigative Jounalism	0Vasil	566368379	9	FALSE	FALSE	2012-04-29 14:54:59+00:00	Vasil Zelenák	unknown
49	114301066	veronika	Yes	User	Investigative Jounalism	zubacova	114301066	117	FALSE	FALSE	2010-02-14 22:50:03+00:00	veronika	right
50	432380933	ac24	Yes	Web	EV_report	AC24cz	432380933	2817	FALSE	FALSE	2011-12-09 10:14:48+00:00	ac24	unknown
51	3300475865	Aeronet	Yes	Web	EV_report	aeronet_cz	3300475865	2255	FALSE	FALSE	2015-05-27 14:36:44+00:00	Aeronet	unknown
52	2520113888	Anarchisticka Federace	Yes	Web	EV_report	afederace	2520113888	1767	FALSE	FALSE	2014-05-24 10:36:02+00:00	Anarchisticka Federace	unknown
53	4514360315	C□asopis S□ifra	Yes	Web	EV_report	casopis_sifra	4514360315	175	FALSE	FALSE	2015-12-17 13:49:26+00:00	C□asopis S□ifra	unknown
54	1073959114395533312	Narodni Noviny	Yes	Web	EV_report	NarodniNoviny	1073959114395533313	281	FALSE	FALSE	2018-12-15 15:13:00+00:00	Narodni Noviny	unknown
55	716931722068303872	Nejvic Info	Yes	Web	EV_report	nejvicinfo	716931722068303872	3	FALSE	FALSE	2016-04-04 10:13:37+00:00	Nejvic Info	unknown
56	349050864	Parlamentni Listy	Yes	Web	EV_report	parlamentky_cz	349050864	6646	FALSE	FALSE	2011-08-05 13:18:34+00:00	Parlamentni Listy	unknown
57	966901314	Pravy prostor	Yes	Web	EV_report	pravyprostor	966901314	690	FALSE	FALSE	2012-11-23 22:01:39+00:00	Pravy prostor	right
58	1323081480	Protiproud	Yes	Web	EV_report	Protiproud	1323081480	1584	FALSE	FALSE	2013-04-02 19:11:05+00:00	Protiproud	unknown
59	3298978576	Realita dne	Yes	Web	EV_report	RealitaDne	3298978576	898	FALSE	FALSE	2015-05-26 07:53:52+00:00	Realita dne	unknown
60	401374610	Reformy.cz	Yes	Web	EV_report	ReformyCZ	401374610	470	FALSE	FALSE	2011-10-30 13:08:22+00:00	Reformy.cz	unknown
61	29321965	Ve□k sve□tla	Yes	Web	EV_report	osud	29321965	345	FALSE	TRUE	2009-04-06 23:14:52+00:00	Ve□k sve□tla	unknown
62	3169820787	VIP noviny	Yes	Web	EV_report	VipNoviny	3169820787	16	FALSE	FALSE	2015-04-15 12:05:05+00:00	VIP noviny	unknown
63	883255556261236736	Vlastenecke Noviny	Yes	Web	EV_report	velicka_radek	883255556261236736	91	FALSE	FALSE	2017-07-07 09:25:09+00:00	Vlastenecke Noviny	right
64	3042273185	dojnice	Yes	User	Newspaper Article - Investigative	dojnice	3042273185	36573	FALSE	FALSE	2015-02-17 11:00:02+00:00	dojnice	right
65	975641897350942720	jietienming	Yes	User	Newspaper Article - Investigative	jietienming	975641897350942720	55192	FALSE	FALSE	2018-03-19 07:55:29+00:00	jietienming	right
66	485539869	vvetvicka	Yes	User	Newspaper Article - Investigative	VVetvicka	485539869	17066	FALSE	FALSE	2012-02-07 09:35:44+00:00	vvetvicka	right
67	1316388026835259392	Jsem Zdesena	Yes	User	Newspaper Article - Investigative	JZdesena	1316388026835259393	3813	FALSE	FALSE	2020-10-14 14:39:15+00:00	Jsem Zdesena	unknown

B List of Politicians

B.1 Politicians with Twitter

	full_name	nominating_party	policical_affiliation	in_2021	has_twitter	in_2017	eu_position	lrgen	nickname	author_id_corrected	followers_count	verified	protected	created_at_account	political_nickname	political_tweet_count
0	Věra Adámková	ANO	ANO	1	1	0	4.4814816	4.6923075	adamkova_vera	927507487443574784	333	FALSE	FALSE	2017-11-06 12:06:32+00:00	adamkova_vera	167
1	Andrej Babiš	ANO	ANO	1	1	0	4.4814816	4.6923075	AndrejBabis	713035525	487962	TRUE	FALSE	2012-07-23 20:12:03+00:00	AndrejBabis	17928
2	Ondřej Babka	ANO	ANO	1	1	0	4.4814816	4.6923075	OndrejBabka	1448435372	292	FALSE	FALSE	2013-05-22 09:28:13+00:00	OndrejBabka	250
3	Ivan Bartoš	Piráti	Piráti	1	1	0	6.1153846	4.2800002	PiratIvanBartos	413938409	143820	FALSE	FALSE	2011-11-16 12:45:04+00:00	PiratIvanBartos	3269
4	Jan Bartošek	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	honzabartosek	2578139028	10576	FALSE	FALSE	2014-06-20 06:23:09+00:00	honzabartosek	4744
5	Jan Bauer	ODS	ODS	1	1	0	3.7777777	7.7777777	BauerJan_pt	1107427370	288	FALSE	FALSE	2013-01-20 22:10:08+00:00	BauerJan_pt	23
6	Martin Baxa	ODS	ODS	1	1	0	3.7777777	7.7777777	MartinBaxa2	960172372514037764	6517	FALSE	FALSE	2018-02-04 15:25:07+00:00	MartinBaxa2	663
7	Petr Beitl	ODS	ODS	1	1	0	3.7777777	7.7777777	PetrBeitl	3303646737	500	FALSE	FALSE	2015-05-30 13:28:30+00:00	PetrBeitl	374
8	Josef Bělica	ANO	ANO	1	1	0	4.4814816	4.6923075	JosefBelica	723440218938822657	73	FALSE	FALSE	2016-04-22 09:16:03+00:00	JosefBelica	76
9	Pavel Bělobrádek	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	PavelBelobradek	501746014	37187	FALSE	FALSE	2012-02-24 12:50:40+00:00	PavelBelobradek	29414
10	Romana Bělohlávková	KDU-ČSL	BEZPP	1	1	0	6.2222223	5.8888888	RBelohlavkova	1446899317852327936	201	FALSE	FALSE	2021-10-09 18:05:24+00:00	RBelohlavkova	87
11	Marek Benda	ODS	ODS	1	1	0	3.7777777	7.7777777	marekbenda2013	1857023965	1760	FALSE	FALSE	2013-09-12 10:34:25+00:00	marekbenda2013	49
12	Petr Bendl	ODS	ODS	1	1	0	3.7777777	7.7777777	bendl_petr	1244899266331660288	629	FALSE	FALSE	2020-03-31 08:08:50+00:00	bendl_petr	618
13	Ondřej Benešík	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	OndrejBenesik	1851115476	187	FALSE	FALSE	2013-09-10 10:59:47+00:00	OndrejBenesik	3
14	Jan Berki	STAN	SLK	1	1	0	6.5185184	6.2692308	BerkiJan	1478363127716712450	276	FALSE	FALSE	2022-01-04 13:50:41+00:00	BerkiJan	73
15	Jana Berkovcová	ANO	ANO	1	1	0	4.4814816	4.6923075	JBerkovcova	1488890354577416199	29	FALSE	FALSE	2022-02-02 15:01:58+00:00	JBerkovcova	2
16	Josef Bernard	STAN	BEZPP	1	1	0	6.5185184	6.2692308	BernardHejtman	757933437185556480	385	FALSE	FALSE	2016-07-26 13:39:48+00:00	BernardHejtman	10
17	Stanislav Blaha	ODS	ODS	1	1	0	3.7777777	7.7777777	StanislavBlaha	155175681	1909	FALSE	FALSE	2010-06-13 10:56:22+00:00	StanislavBlaha	972
18	Pavel Blažek	ODS	ODS	1	1	0	3.7777777	7.7777777	blazek_p	1475244167597076489	877	FALSE	FALSE	2021-12-26 23:17:50+00:00	blazek_p	18
19	Richard Brabec	ANO	ANO	1	1	0	4.4814816	4.6923075	RibraRichard	1487106288	8216	FALSE	FALSE	2013-06-06 07:36:31+00:00	RibraRichard	1269
20	Lubomír Brož	ANO	ANO	1	1	0	4.4814816	4.6923075	LuboBroz	564836811	262	FALSE	FALSE	2012-04-27 16:50:33+00:00	LuboBroz	151
21	Jan Bureš	ODS	ODS	1	1	0	3.7777777	7.7777777	J_Bures	1742217266	95	FALSE	FALSE	2013-09-07 06:49:17+00:00	J_Bures	403
22	Jaroslav Bžoch	ANO	ANO	1	1	0	4.4814816	4.6923075	JaroslavBzoch	518897308	771	FALSE	FALSE	2012-03-08 21:31:34+00:00	JaroslavBzoch	313
23	Jiří Carbol	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	CarbolJiri	2650400271	248	FALSE	FALSE	2014-06-28 15:19:25+00:00	CarbolJiri	47
24	Josef Cogan	STAN	STAN	1	1	0	6.5185184	6.2692308	JosefCogan	902543504173355009	406	FALSE	FALSE	2017-08-29 14:48:34+00:00	JosefCogan	63
25	Jana Černochová	ODS	ODS	1	1	0	3.7777777	7.7777777	jana_cernochova	861952362491019264	26570	FALSE	FALSE	2017-05-09 14:33:52+00:00	jana_cernochova	2448
26	Eva Decroix	ODS	ODS	1	1	0	3.7777777	7.7777777	eva_decroix	3676416317	1085	FALSE	FALSE	2015-09-16 16:12:59+00:00	eva_decroix	39
27	Klára Dostálová	ANO	BEZPP	1	1	0	4.4814816	4.6923075	DostalovaK	730414396372045825	4702	FALSE	FALSE	2016-05-11 15:08:57+00:00	DostalovaK	778
28	Lenka Dražilová	ANO	ANO	1	1	0	4.4814816	4.6923075	LenkaDrazilova	1221893219514028036	87	FALSE	FALSE	2020-01-27 20:31:06+00:00	LenkaDrazilova	3
29	Tomáš Dubský	STAN	STAN	1	1	0	6.5185184	6.2692308	TomasDubskySTAN	1498681176067870724	63	FALSE	FALSE	2022-03-01 15:27:12+00:00	TomasDubskySTAN	28
30	Martin Exner	STAN	STAN	1	1	0	6.5185184	6.2692308	Exner_STAN	1506614064096624648	93	FALSE	FALSE	2022-03-23 12:55:25+00:00	Exner_STAN	35
31	Jan Farský	STAN	STAN	1	1	0	6.5185184	6.2692308	JanFar_sky	721019072528400384	26513	FALSE	FALSE	2016-04-15 16:55:17+00:00	JanFar_sky	3958
32	Milan Feranec	ANO	ANO	1	1	0	4.4814816	4.6923075	MilanFeranec	834400274081013760	46	FALSE	FALSE	2017-02-22 13:51:42+00:00	MilanFeranec	13
33	Petr Fiala	ODS	ODS	1	1	0	3.7777777	7.7777777	P_Fiala	1464550303	240061	TRUE	FALSE	2013-05-28 12:15:54+00:00	P_Fiala	6283
34	Radim Fiala	SPD	SPD	1	1	0	1.4814814	8.8461542	RadimFialacz	2312290608	4133	FALSE	FALSE	2014-01-26 18:40:44+00:00	RadimFialacz	658
35	Petr Fifka	ODS	ODS	1	1	0	3.7777777	7.7777777	PetrFifka	1450072549266792451	197	FALSE	FALSE	2021-10-18 12:13:42+00:00	PetrFifka	48
36	Romana Fischerová	ANO	ANO	1	1	0	4.4814816	4.6923075	romana_fischer	1568157739	36	FALSE	FALSE	2013-07-04 12:48:22+00:00	romana_fischer	180
37	Josef Flek	STAN	STAN	1	1	0	6.5185184	6.2692308	joseffleki	1484123413631451139	125	FALSE	FALSE	2022-01-20 11:19:50+00:00	joseffleki	70
38	Jaroslav Foldyna	SPD	SPD	1	1	0	1.4814814	8.8461542	FoldynaJaroslav	3918690617	5853	FALSE	FALSE	2015-10-10 13:34:02+00:00	FoldynaJaroslav	1609
39	Petr Gazdík	STAN	STAN	1	1	0	6.5185184	6.2692308	petrgazdik	444671520	25764	FALSE	FALSE	2011-12-23 14:16:52+00:00	petrgazdik	2607
40	Pavla Golasowská	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	pgolasowska	752261833264889857	152	FALSE	FALSE	2016-07-10 22:02:52+00:00	pgolasowska	53
41	Karel Haas	ODS	ODS	1	1	0	3.7777777	7.7777777	karel_haas	3202192527	530	FALSE	FALSE	2015-04-24 20:42:47+00:00	karel_haas	1949
42	Martin Hájek	STAN	STAN	1	1	0	6.5185184	6.2692308	marthajek	759412883654643712	3141	FALSE	FALSE	2016-07-30 15:38:35+00:00	marthajek	79
43	Matěj Ondřej Havel	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	m_o_havel	1359909737479995394	455	FALSE	FALSE	2021-02-11 16:58:56+00:00	m_o_havel	160
44	Karel Havlíček	ANO	BEZPP	1	1	0	4.4814816	4.6923075	KarelHavlicek_	1105851826702897152	31786	FALSE	FALSE	2019-03-13 15:23:16+00:00	KarelHavlicek_	4126
45	Jiří Havránek	ODS	ODS	1	1	0	3.7777777	7.7777777	j_havranek	1387759009684467719	600	FALSE	FALSE	2021-04-29 13:21:54+00:00	j_havranek	293
46	Šimon Heller	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	hellersimon	2556901640	912	FALSE	FALSE	2014-06-09 13:54:31+00:00	hellersimon	422
47	Igor Hendrych	ANO	ANO	1	1	0	4.4814816	4.6923075	IgorHendrych	1478086020629417990	21	FALSE	FALSE	2022-01-03 19:29:20+00:00	IgorHendrych	7
48	Radim Holiš	ANO	ANO	1	1	0	4.4814816	4.6923075	HolisRadim	1387365881009819651	389	FALSE	FALSE	2021-04-28 11:21:17+00:00	HolisRadim	191
49	Jiří Horák	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	JirHorak	1356686635224748034	1502	FALSE	FALSE	2021-02-02 19:31:47+00:00	JirHorak	175
50	Jan Jakob	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	Jan_Jakob	322647291	2455	FALSE	FALSE	2011-06-23 14:32:30+00:00	Jan_Jakob	460

51	Jakub Janda	ODS	ODS	1	1	0	3.7777777	7.7777777	jandysj	131825361	3076	FALSE	FALSE	2010-04-11 13:00:48+00:00	jandysj	644
52	Marie Jílková	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	MarieJilkova	1406520982223966211	1133	FALSE	FALSE	2021-06-20 07:55:16+00:00	MarieJilkova	226
53	Aleš Juchelka	ANO	ANO	1	1	0	4.4814816	4.6923075	juchelkaa	2800234201	796	FALSE	FALSE	2014-09-09 16:35:10+00:00	juchelkaa	84
54	Marian Jurečka	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	MJureka	634566367	51713	FALSE	FALSE	2012-07-13 13:10:43+00:00	MJureka	9808
55	Vít Kaňkovský	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	VitKAKOVSK1	1171797628587302912	709	FALSE	FALSE	2019-09-11 14:48:41+00:00	VitKAKOVSK1	300
56	Pavel Kašník	ODS	ODS	1	1	0	3.7777777	7.7777777	KasnikPavel	1376432221670739969	178	FALSE	FALSE	2021-03-29 07:13:21+00:00	KasnikPavel	123
57	Zdeněk Kettner	SPD	SPD	1	1	0	1.4814814	8.8461542	z_kettner	1492959196568068100	37	FALSE	FALSE	2022-02-13 20:30:31+00:00	z_kettner	151
58	Pavel Klíma	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	klima_pavel	2450877786	540	FALSE	FALSE	2014-04-18 05:21:34+00:00	klima_pavel	405
59	Klára Kocmanová	Piráti	Piráti	1	1	0	6.1153846	4.2800002	KlaraKocmanova	1102505818166050816	3366	FALSE	FALSE	2019-03-04 09:47:25+00:00	KlaraKocmanova	201
60	Michael Kohajda	KDU-ČSL	BEZPP	1	1	0	6.2222223	5.8888888	MichaelKohajda	2849555872	350	FALSE	FALSE	2014-10-29 09:20:18+00:00	MichaelKohajda	264
61	Ondřej Kolář	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	OndrejKolar6	826804721415553024	5483	FALSE	FALSE	2017-02-01 14:49:41+00:00	OndrejKolar6	996
62	Martin Kolovratník	ANO	ANO	1	1	0	4.4814816	4.6923075	kolovratnikm	301436730	2327	TRUE	FALSE	2011-05-19 13:31:19+00:00	kolovratnikm	6618
63	Radek Koten	SPD	SPD	1	1	0	1.4814814	8.8461542	kotenSPD	936236510055206917	50	FALSE	FALSE	2017-11-30 14:12:33+00:00	kotenSPD	16
64	Věra Kovářová	STAN	STAN	1	1	0	6.5185184	6.2692308	v_kovarova	803889553828356096	3642	FALSE	FALSE	2016-11-30 09:13:00+00:00	v_kovarova	1311
65	Václav Král	ODS	ODS	1	1	0	3.7777777	7.7777777	KralVaclav	1775606426	27	FALSE	FALSE	2013-09-07 20:58:59+00:00	KralVaclav	11
66	Robert Králíček	ANO	ANO	1	1	0	4.4814816	4.6923075	psprobertkrali1	1052536495242788864	296	FALSE	FALSE	2018-10-17 12:27:10+00:00	psprobertkrali1	368
67	Karel Krejza	ODS	ODS	1	1	0	3.7777777	7.7777777	KrejzaODS	864502111333220354	102	FALSE	FALSE	2017-05-16 15:25:39+00:00	KrejzaODS	0
68	Jana Krutáková	STAN	STAN	1	1	0	6.5185184	6.2692308	janakrut	1007594183417266176	313	FALSE	FALSE	2018-06-15 12:02:28+00:00	janakrut	115
69	Roman Kubíček	ANO	ANO	1	1	0	4.4814816	4.6923075	roman_kubicek	833738098211164163	68	FALSE	FALSE	2017-02-20 18:00:27+00:00	roman_kubicek	130
70	Michal Kučera	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	MichKucera	1704708763	2306	FALSE	FALSE	2013-08-27 13:20:09+00:00	MichKucera	2003
71	Jan Kuchař	STAN	STAN	1	1	0	6.5185184	6.2692308	JanKuchar21	1427390514891001865	7	FALSE	FALSE	2021-08-16 22:03:24+00:00	JanKuchar21	6
72	Martin Kukla	ANO	ANO	1	1	0	4.4814816	4.6923075	MartinKukla6	1252884619612942337	126	FALSE	FALSE	2020-04-22 09:00:26+00:00	MartinKukla6	190
73	Martin Kupka	ODS	ODS	1	1	0	3.7777777	7.7777777	makupka	1778249820	24290	FALSE	FALSE	2013-09-07 21:36:13+00:00	makupka	1311
74	Jan Lacina	STAN	STAN	1	1	0	6.5185184	6.2692308	j_lacina	828627875913936896	646	FALSE	FALSE	2017-02-06 15:34:15+00:00	j_lacina	973
75	Helena Langšádlová	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	H_Langsadlova	710033915034144768	5605	FALSE	FALSE	2016-03-16 09:24:11+00:00	H_Langsadlova	2706
76	Petr Letocha	STAN	STAN	1	1	0	6.5185184	6.2692308	petr_letocha	740878568734007296	254	FALSE	FALSE	2016-06-09 12:09:50+00:00	petr_letocha	101
77	Martina Lisová	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	LisovaMartina	1268260179008765958	53	FALSE	FALSE	2020-06-03 19:16:21+00:00	LisovaMartina	2
78	Ondřej Lochman	STAN	STAN	1	1	0	6.5185184	6.2692308	ondrejlochman	2935783559	384	FALSE	FALSE	2014-12-21 20:03:20+00:00	ondrejlochman	181
79	Ivana Mádlová	ANO	ANO	1	1	0	4.4814816	4.6923075	MadlovaIvana	1435495896263929862	51	FALSE	FALSE	2021-09-08 06:52:01+00:00	MadlovaIvana	24
80	Martin Major	ODS	ODS	1	1	0	3.7777777	7.7777777	MartinMajor13	1239997644572962817	12	FALSE	FALSE	2020-03-17 19:31:06+00:00	MartinMajor13	3
81	Taťána Malá	ANO	ANO	1	1	0	4.4814816	4.6923075	TatanaMala	3043922538	686	FALSE	FALSE	2015-02-26 16:11:00+00:00	TatanaMala	86
82	Karla Maříková	SPD	SPD	1	1	0	1.4814814	8.8461542	MarikovaKarla	792277937630437376	694	FALSE	FALSE	2016-10-29 08:12:35+00:00	MarikovaKarla	93
83	Jiří Mašek	ANO	ANO	1	1	0	4.4814816	4.6923075	MasekMudr	1478336857326989316	418	FALSE	FALSE	2022-01-04 12:06:01+00:00	MasekMudr	197
84	Lubomír Metnar	ANO	BEZPP	1	1	0	4.4814816	4.6923075	metnarl	1044587777990569984	5147	FALSE	FALSE	2018-09-25 14:01:48+00:00	metnarl	858
85	Jakub Michálek	Piráti	Piráti	1	1	0	6.1153846	4.2800002	JakubMichalek19	2815507955	23992	FALSE	FALSE	2014-10-08 14:36:50+00:00	JakubMichalek19	1260
86	Jana Mračková Vildume	ANO	ANO	1	1	0	4.4814816	4.6923075	JVildumetzova	810864580310290432	1927	FALSE	FALSE	2016-12-19 15:09:15+00:00	JVildumetzova	895
87	Tomáš Müller	STAN	STAN	1	1	0	6.5185184	6.2692308	StanMuller	1365202336122101760	245	FALSE	FALSE	2021-02-26 07:30:49+00:00	StanMuller	138
88	Vojtěch Munzar	ODS	ODS	1	1	0	3.7777777	7.7777777	munzar_vojtech	826541636075323392	1106	FALSE	FALSE	2017-01-31 21:24:17+00:00	munzar_vojtech	444
89	Patrik Nacher	ANO	BEZPP	1	1	0	4.4814816	4.6923075	PatrikNacher	50296368	7985	FALSE	FALSE	2009-06-24 12:55:14+00:00	PatrikNacher	12685
90	Hana Naiclerová	STAN	STAN	1	1	0	6.5185184	6.2692308	naiclerova	1709257627	188	FALSE	FALSE	2013-08-29 05:43:42+00:00	naiclerova	198
91	Jiří Navrátil	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	Jiri_Navratil_	1356689623955742721	532	FALSE	FALSE	2021-02-02 19:43:24+00:00	Jiri_Navratil_	224
92	Zdenka Němečková Crl	ODS	ODS	1	1	0	3.7777777	7.7777777	ZCrkvenjas	1004728862931070976	2183	FALSE	FALSE	2018-06-07 14:16:42+00:00	ZCrkvenjas	767
93	Marek Novák	ANO	ANO	1	1	0	4.4814816	4.6923075	ca340354	908392867	171	FALSE	FALSE	2012-10-27 15:57:18+00:00	ca340354	281
94	Nina Nováková	KDU-ČSL	BEZPP	1	1	0	6.2222223	5.8888888	NinaNovkov1	716623740	92	FALSE	FALSE	2012-07-25 19:32:11+00:00	NinaNovkov1	11
95	Monika Oborná	ANO	ANO	1	1	0	4.4814816	4.6923075	ObornaMonika	2455153291	513	FALSE	FALSE	2014-04-20 14:46:30+00:00	ObornaMonika	196
96	Hayato Okamura	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	HayatoOkamura	1067037528920940544	11732	FALSE	FALSE	2018-11-26 12:49:06+00:00	HayatoOkamura	6467
97	Tomio Okamura	SPD	SPD	1	1	0	1.4814814	8.8461542	tomio_cz	1710527172	43101	FALSE	FALSE	2013-08-29 17:24:17+00:00	tomio_cz	7140
98	Ladislav Okleštěk	ANO	ANO	1	1	0	4.4814816	4.6923075	OklestekLa	837941892914561024	709	FALSE	FALSE	2017-03-04 08:24:50+00:00	OklestekLa	223
99	Eliška Olšáková	STAN	STAN	1	1	0	6.5185184	6.2692308	OlsakovaE	1480917379148308488	198	FALSE	FALSE	2022-01-11 15:00:13+00:00	OlsakovaE	82
100	Michaela Opltová	STAN	STAN	1	1	0	6.5185184	6.2692308	OpltovaM	1486773477990449164	351	FALSE	FALSE	2022-01-27 18:50:07+00:00	OpltovaM	43

101	Jana Pastuchová	ANO	ANO	1	1	0	4.4814816	4.6923075	pastuchovaANO	825995759166316548	426	TRUE	FALSE	2017-01-30 09:15:10+00:00	pastuchovaANO	150
102	Markéta Pekarová Adar	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	market_a	128663448	131900	FALSE	FALSE	2010-04-01 20:31:01+00:00	market_a	6382
103	Tom Philipp	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	MUDr_TomPhilipp	1347679757656330240	1572	FALSE	FALSE	2021-01-08 23:01:52+00:00	MUDr_TomPhilipp	566
104	Pavla Pivoňka Vaňková	STAN	STAN	1	1	0	6.5185184	6.2692308	PavlaPivonka	1362726070395486213	150	FALSE	FALSE	2021-02-19 11:30:06+00:00	PavlaPivonka	33
105	Jaroslava Pokorná Jern	ANO	ANO	1	1	0	4.4814816	4.6923075	JermanovaStKraj	1241989542225248259	922	FALSE	FALSE	2020-03-23 07:27:07+00:00	JermanovaStKraj	824
106	David Pražák	ANO	ANO	1	1	0	4.4814816	4.6923075	prazakzesemil	1330631196989075464	48	FALSE	FALSE	2020-11-22 21:56:27+00:00	prazakzesemil	80
107	Karel Rais	ANO	ANO	1	1	0	4.4814816	4.6923075	KarelRais	2785281790	132	FALSE	FALSE	2014-09-26 10:58:10+00:00	KarelRais	71
108	Vít Rakušan	STAN	STAN	1	1	0	6.5185184	6.2692308	Vit_Rakusan	715102844270080000	128283	FALSE	FALSE	2016-03-30 09:06:18+00:00	Vit_Rakusan	2118
109	Michael Rataj	STAN	STAN	1	1	0	6.5185184	6.2692308	MRataj	958037196698681344	33	FALSE	FALSE	2018-01-29 18:00:41+00:00	MRataj	23
110	Olga Richterová	Piráti	Piráti	1	1	0	6.1153846	4.2800002	olgarichterova	4793382383	25600	FALSE	FALSE	2016-01-13 10:48:22+00:00	olgarichterova	2967
111	Radek Rozvoral	SPD	SPD	1	1	0	1.4814814	8.8461542	RadekRozvoral	806192489430454272	433	FALSE	FALSE	2016-12-06 17:44:02+00:00	RadekRozvoral	1856
112	Pavel Růžička	ANO	ANO	1	1	0	4.4814816	4.6923075	ruzickapavel70	927516056	259	FALSE	FALSE	2012-11-05 12:27:03+00:00	ruzickapavel70	448
113	Petr Sadovský	ANO	ANO	1	1	0	4.4814816	4.6923075	PetrSadovskyp	976378570359693312	72	FALSE	FALSE	2018-03-21 08:42:46+00:00	PetrSadovskyp	22
114	Alena Schillerová	ANO	BEZPP	1	1	0	4.4814816	4.6923075	alenaschillerov	1408164626	52739	FALSE	FALSE	2013-05-06 16:32:47+00:00	alenaschillerov	5083
115	Jan Skopeček	ODS	ODS	1	1	0	3.7777777	7.7777777	Jan_Skopecek	1869336583	14363	FALSE	FALSE	2013-09-15 21:41:50+00:00	Jan_Skopecek	4879
116	Karel Smetana	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	Smetana_Karel	1220800022	197	FALSE	FALSE	2013-02-26 08:00:05+00:00	Smetana_Karel	137
117	Pavel Staněk	ODS	ODS	1	1	0	3.7777777	7.7777777	Stanek_Pavel	1861314691	83	FALSE	FALSE	2013-09-13 17:54:04+00:00	Stanek_Pavel	46
118	Zbyněk Stanjura	ODS	ODS	1	1	0	3.7777777	7.7777777	Zbynek_Stanjura	1282857414	27197	FALSE	FALSE	2013-03-20 10:04:02+00:00	Zbynek_Stanjura	693
119	Robert Stržínek	ANO	ANO	1	1	0	4.4814816	4.6923075	robertstrzinek	1546251498	49	FALSE	FALSE	2013-06-25 17:39:18+00:00	robertstrzinek	305
120	Bohuslav Svoboda	ODS	ODS	1	1	0	3.7777777	7.7777777	BohuslavSvoboda	1854474325	2759	FALSE	FALSE	2013-09-11 14:10:23+00:00	BohuslavSvoboda	270
121	Pavel Svoboda	TOP 9.00	BEZPP	1	1	0	6.6666665	7.4074073	1PavelSvoboda	2578600004	6175	TRUE	FALSE	2014-06-20 12:32:55+00:00	1PavelSvoboda	6826
122	Lucie Šafránková	SPD	SPD	1	1	0	1.4814814	8.8461542	safrankovaspd	1265936777673691136	98	FALSE	FALSE	2020-05-28 09:24:11+00:00	safrankovaspd	19
123	David Šimek	KDU-ČSL	Nestran.	1	1	0	6.2222223	5.8888888	David_Simek_01	1448314956181610499	103	FALSE	FALSE	2021-10-13 15:50:17+00:00	David_Simek_01	48
124	Julius Špičák	ANO	ANO	1	1	0	4.4814816	4.6923075	spicakjulius	1473796981478805509	234	FALSE	FALSE	2021-12-22 23:26:05+00:00	spicakjulius	18
125	David Štolpa	ANO	ANO	1	1	0	4.4814816	4.6923075	DavidStolpa	2289246826	51	FALSE	FALSE	2014-01-18 08:22:50+00:00	DavidStolpa	14
126	Róbert Teleky	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	RobertTeleky	1458490415565398025	85	FALSE	FALSE	2021-11-10 17:43:27+00:00	RobertTeleky	6
127	Antonín Tesařík	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	tesarik_antonin	1364680529833054209	302	FALSE	FALSE	2021-02-24 20:56:25+00:00	tesarik_antonin	63
128	Karel Tureček	ANO	ANO	1	1	0	4.4814816	4.6923075	karel_turecek	1478291772451303424	180	FALSE	FALSE	2022-01-04 09:07:21+00:00	karel_turecek	87
129	Barbora Urbanová	STAN	STAN	1	1	0	6.5185184	6.2692308	BaraUrbanova	578169668	3752	FALSE	FALSE	2012-05-12 15:53:58+00:00	BaraUrbanova	5414
130	Vlastimil Válek	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	vlvalek	1930406870	27150	TRUE	FALSE	2013-10-03 11:35:15+00:00	vlvalek	2202
131	Helena Válková	ANO	ANO	1	1	0	4.4814816	4.6923075	HelenaValkova	3001396720	1299	FALSE	FALSE	2015-01-27 13:26:17+00:00	HelenaValkova	68
132	Radovan Vích	SPD	SPD	1	1	0	1.4814814	8.8461542	IngVich	3435550491	207	FALSE	FALSE	2015-08-22 15:48:26+00:00	IngVich	1796
133	Lukáš Vlček	STAN	STAN	1	1	0	6.5185184	6.2692308	VlcekSTAN	1453668751459618816	229	FALSE	FALSE	2021-10-28 10:24:37+00:00	VlcekSTAN	81
134	Milada Voborská	STAN	STAN	1	1	0	6.5185184	6.2692308	MiladaVoborska	1479717407157628933	85	FALSE	FALSE	2022-01-08 07:32:00+00:00	MiladaVoborska	104
135	Viktor Vojtko	STAN	STAN	1	1	0	6.5185184	6.2692308	vvojtko	74819660	669	FALSE	FALSE	2009-09-16 19:48:59+00:00	vvojtko	4029
136	Jan Volný	ANO	ANO	1	1	0	4.4814816	4.6923075	JanVolnyANO	2833827977	89	FALSE	FALSE	2014-10-16 10:46:31+00:00	JanVolnyANO	23
137	Radek Vondráček	ANO	ANO	1	1	0	4.4814816	4.6923075	vondraczech	710583823122178048	8243	TRUE	FALSE	2016-03-17 21:49:20+00:00	vondraczech	982
138	Ivo Vondrák	ANO	ANO	1	1	0	4.4814816	4.6923075	ivondrak	503140125	4819	FALSE	FALSE	2012-02-25 15:15:20+00:00	ivondrak	4192
139	Marek Výborný	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	MarekVyborny	892740558577422336	10512	FALSE	FALSE	2017-08-02 13:35:10+00:00	MarekVyborny	1660
140	Renáta Zajíčková	ODS	ODS	1	1	0	3.7777777	7.7777777	RenataZajickova	1124195387823337472	472	FALSE	FALSE	2019-05-03 06:14:01+00:00	RenataZajickova	436
141	Miroslav Zborovský	KDU-ČSL	KDU-ČSL	1	1	0	6.2222223	5.8888888	MZborovsky	1357414545866784771	463	FALSE	FALSE	2021-02-04 19:44:23+00:00	MZborovsky	369
142	Michal Zuna	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	michal_zuna	1142464608134995968	446	FALSE	FALSE	2019-06-22 16:09:23+00:00	michal_zuna	94
143	Pavel Žáček	ODS	ODS	1	1	0	3.7777777	7.7777777	PavelZacek_69	1364576560792141834	2786	FALSE	FALSE	2021-02-24 14:05:33+00:00	PavelZacek_69	470
144	Marek Ženíšek	TOP 9.00	TOP 9.00	1	1	0	6.6666665	7.4074073	zenisek_m	1898366484	13892	FALSE	FALSE	2013-09-23 20:58:23+00:00	zenisek_m	7850
145	Dana Balcarová	Piráti	Piráti	0	1	1	6.1153846	4.2800002	DanaBalcarova	967000764852899840	1437	FALSE	FALSE	2018-02-23 11:38:43+00:00	DanaBalcarova	720
146	Lukáš Bartoň	Piráti	Piráti	0	1	1	6.1153846	4.2800002	BartonPirat	1103609219733962752	529	FALSE	FALSE	2019-03-07 10:51:56+00:00	BartonPirat	173
147	Jan Birke	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	Honza_Birke	832148988967124992	1023	FALSE	FALSE	2017-02-16 08:45:54+00:00	Honza_Birke	90
148	Jiří Bláha	ANO	BEZPP	0	1	1	4.4814816	4.6923075	HradecakBlaha	1361297827234775043	137	FALSE	FALSE	2021-02-15 12:55:37+00:00	HradecakBlaha	214
149	Lukáš Černohorský	Piráti	Piráti	0	1	1	6.1153846	4.2800002	cernohorskyl	3119858494	1587	FALSE	FALSE	2015-03-26 21:27:16+00:00	cernohorskyl	831
150	Jan Čižinský	KDU-ČSL	KDU-ČSL	0	1	1	6.2222223	5.8888888	jancizinsky	314564202	8350	FALSE	FALSE	2011-06-10 13:20:08+00:00	jancizinsky	1488

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151	Jiří Dolejš	KSČM	KSČM	0	1	1	2.3703704	1.1481482	DolejsJiri	1914170347	6224	FALSE	FALSE	2013-09-28 13:17:30+00:00	DolejsJiri	52961
152	Petr Dolínek	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	DolinekPetr	2408706744	1086	FALSE	FALSE	2014-03-24 09:42:16+00:00	DolinekPetr	399
153	František Elfmark	Piráti	BEZPP	0	1	1	6.1153846	4.2800002	ElfmarkF	2888458138	689	FALSE	FALSE	2014-11-22 22:17:01+00:00	ElfmarkF	1243
154	Dominik Feri	TOP 9.00	TOP 9.00	0	1	1	6.6666665	7.4074073	DominikFeri	2869270971	185729	FALSE	FALSE	2014-11-09 17:52:30+00:00	DominikFeri	4187
155	Mikuláš Ferjenčík	Piráti	Piráti	0	1	1	6.1153846	4.2800002	Mikiferjencik	50255554	24419	FALSE	FALSE	2009-06-24 08:48:43+00:00	Mikiferjencik	2851
156	Vojtěch Filip	KSČM	KSČM	0	1	1	2.3703704	1.1481482	vojtafilip	839771819469078529	5669	FALSE	FALSE	2017-03-09 09:36:18+00:00	vojtafilip	514
157	Alena Gajdůšková	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	GajduskovaAlena	397149854	2509	FALSE	FALSE	2011-10-24 09:30:05+00:00	GajduskovaAlena	9272
158	Josef Hájek	ANO	ANO	0	1	1	4.4814816	4.6923075	Pephaj	2967472995	47	FALSE	FALSE	2015-01-08 09:32:03+00:00	Pephaj	10
159	Jan Hamáček	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	jhamacek	20664874	93848	FALSE	FALSE	2009-02-12 09:44:43+00:00	jhamacek	4052
160	Tomáš Hanzel	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	Hanzel_Tom	1007537285460619264	207	FALSE	FALSE	2018-06-15 08:16:22+00:00	Hanzel_Tom	15
161	Milan Hnilička	ANO	BEZPP	0	1	1	4.4814816	4.6923075	MilanHnilicka	935120546173513728	1959	FALSE	FALSE	2017-11-27 12:18:06+00:00	MilanHnilicka	402
162	Jaroslav Holík	SPD	SPD	0	1	1	1.4814814	8.8461542	holik_j	1847666600	17	FALSE	FALSE	2013-09-09 15:42:16+00:00	holik_j	0
163	Radek Holomčík	Piráti	Piráti	0	1	1	6.1153846	4.2800002	RadekHolomcik	483998029	1008	FALSE	FALSE	2012-02-05 16:34:16+00:00	RadekHolomcik	306
164	Libor Hoppe	ODS	ODS	0	1	1	3.7777777	7.7777777	LiborHoppe	1369683084258467842	18	FALSE	FALSE	2021-03-10 16:14:58+00:00	LiborHoppe	74
165	Tereza Hyťhová	SPD	SPD	0	1	1	1.4814814	8.8461542	THythova	1370731055381110786	1798	FALSE	FALSE	2021-03-13 13:39:28+00:00	THythova	367
166	Milan Chovanec	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	Milan_Chovanec	2827309641	16224	FALSE	FALSE	2014-10-13 12:18:18+00:00	Milan_Chovanec	977
167	Pavel Jelínek	SPD	SPD	0	1	1	1.4814814	8.8461542	PavelJelnek8	1069687236575354880	12	FALSE	FALSE	2018-12-03 20:18:05+00:00	PavelJelnek8	4
168	Martin Jiránek	Piráti	Piráti	0	1	1	6.1153846	4.2800002	MartinJiranek	1267112552	805	FALSE	FALSE	2013-03-14 13:45:32+00:00	MartinJiranek	173
169	Stanislav Juránek	KDU-ČSL	KDU-ČSL	0	1	1	6.2222223	5.8888888	Juranek	190599502	80	FALSE	FALSE	2010-09-14 11:02:05+00:00	Juranek	305
170	Adam Kalous	ANO	ANO	0	1	1	4.4814816	4.6923075	adam_kalous	954320040681189377	75	FALSE	FALSE	2018-01-19 11:50:02+00:00	adam_kalous	27
171	Miroslav Kalousek	TOP 9.00	TOP 9.00	0	1	1	6.6666665	7.4074073	kalousekm	1705781160	267185	TRUE	FALSE	2013-08-27 23:10:13+00:00	kalousekm	15606
172	Václav Klaus	ODS	ODS	0	1	1	3.7777777	7.7777777	vkmladsi	856534141717893120	1323	FALSE	FALSE	2017-04-24 15:43:47+00:00	vkmladsi	796
173	Lukáš Kolářík	Piráti	Piráti	0	1	1	6.1153846	4.2800002	kolarik_lukas	1059388281073426433	728	FALSE	FALSE	2018-11-05 10:13:43+00:00	kolarik_lukas	280
174	František Kopřiva	Piráti	Piráti	0	1	1	6.1153846	4.2800002	FrantisekKopiva	2526008654	2752	FALSE	FALSE	2014-05-26 22:44:39+00:00	FrantisekKopiva	1801
175	Barbora Kořanová	ANO	ANO	0	1	1	4.4814816	4.6923075	koranova_b	827490781720088577	1491	FALSE	FALSE	2017-02-03 12:15:51+00:00	koranova_b	1452
176	Lenka Kozlová	Piráti	Piráti	0	1	1	6.1153846	4.2800002	Kozlova_Pirati	948122974556696576	411	FALSE	FALSE	2018-01-02 09:25:07+00:00	Kozlova_Pirati	113
177	Jaroslav Kytýr	ANO	ANO	0	1	1	4.4814816	4.6923075	JaroslavKytyr	1143955504491880454	45	FALSE	FALSE	2019-06-26 18:53:40+00:00	JaroslavKytyr	25
178	Jan Lipavský	Piráti	Piráti	0	1	1	6.1153846	4.2800002	JanLipavsky	51404691	38917	FALSE	FALSE	2009-06-27 10:28:27+00:00	JanLipavsky	4960
179	Zuzana Majerová Zahra	ODS	ODS	0	1	1	3.7777777	7.7777777	MajerovaZ	847760358676860929	3885	FALSE	FALSE	2017-03-31 10:39:54+00:00	MajerovaZ	508
180	Přemysl Mališ	ANO	ANO	0	1	1	4.4814816	4.6923075	Premysl_Malis	1890495091	18	FALSE	FALSE	2013-09-21 15:08:07+00:00	Premysl_Malis	16
181	Tomáš Martínek	Piráti	Piráti	0	1	1	6.1153846	4.2800002	TomasMartinekCZ	949304340099076096	2524	FALSE	FALSE	2018-01-05 15:39:26+00:00	TomasMartinekCZ	4303
182	Radka Maxová	ANO	ANO	0	1	1	4.4814816	4.6923075	MaxovaRadka	1248322963746717696	606	TRUE	FALSE	2020-04-09 18:53:05+00:00	MaxovaRadka	461
183	Marcela Melková	ANO	ANO	0	1	1	4.4814816	4.6923075	MarcelaMelkova	1359230613866369027	1060	FALSE	FALSE	2021-02-09 20:00:21+00:00	MarcelaMelkova	1507
184	Jiří Mihola	KDU-ČSL	KDU-ČSL	0	1	1	6.2222223	5.8888888	JMihola	1829735718	1936	FALSE	FALSE	2013-09-08 14:17:09+00:00	JMihola	1089
185	Miroslava Němcová	ODS	ODS	0	1	1	3.7777777	7.7777777	Nemcova_Mirka	1737448897	38535	FALSE	FALSE	2013-09-06 21:19:31+00:00	Nemcova_Mirka	359
186	Roman Onderka	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	ROnderka	1272895419291439106	265	FALSE	FALSE	2020-06-16 14:16:35+00:00	ROnderka	327
187	Mikuláš Peksa	Piráti	Piráti	0	1	1	6.1153846	4.2800002	vonpecka	1402424148	6030	TRUE	FALSE	2013-05-04 14:11:52+00:00	vonpecka	5005
188	Robert Pelikán	ANO	ANO	0	1	1	4.4814816	4.6923075	RPelik	2913585059	12916	TRUE	FALSE	2014-12-10 11:00:16+00:00	RPelik	713
189	Ivo Pojezný	KSČM	KSČM	0	1	1	2.3703704	1.1481482	IPojezny	957272304798625793	44	FALSE	FALSE	2018-01-27 15:21:17+00:00	IPojezny	82
190	Ondřej Polanský	Piráti	Piráti	0	1	1	6.1153846	4.2800002	ondrej_polansky	41543322	545	FALSE	FALSE	2009-05-21 06:41:54+00:00	ondrej_polansky	190
191	Jan Pošvář	Piráti	Piráti	0	1	1	6.1153846	4.2800002	PosvarJan	2891796411	525	FALSE	FALSE	2014-11-25 09:49:14+00:00	PosvarJan	542
192	Milan Pour	ANO	ANO	0	1	1	4.4814816	4.6923075	pour_milan	1429777914610995205	3	FALSE	FALSE	2021-08-23 12:10:37+00:00	pour_milan	0
193	Ondřej Profant	Piráti	Piráti	0	1	1	6.1153846	4.2800002	ondrej_profant	545927996	2991	FALSE	FALSE	2012-04-05 12:22:02+00:00	ondrej_profant	6219
194	Pavel Pustějovský	ANO	ANO	0	1	1	4.4814816	4.6923075	chp1530	1473108601	72	FALSE	FALSE	2013-05-31 21:07:01+00:00	chp1530	45
195	Martin Půta	STAN	STAN	0	1	1	6.5185184	6.2692308	MartinPuta	622746371	2838	FALSE	FALSE	2012-06-30 11:45:03+00:00	MartinPuta	1354
196	Miloslav Rozner	SPD	SPD	0	1	1	1.4814814	8.8461542	MiloslavRozner	924304345566498820	8260	FALSE	FALSE	2017-10-28 15:58:23+00:00	MiloslavRozner	2088
197	Jan Řehounek	ANO	ANO	0	1	1	4.4814816	4.6923075	rehounek	3127125448	89	FALSE	FALSE	2015-03-29 18:14:41+00:00	rehounek	43
198	Karel Schwarzenberg	TOP 9.00	TOP 9.00	0	1	1	6.6666665	7.4074073	schwarzenbergk	380270590	299276	FALSE	FALSE	2011-09-26 11:14:02+00:00	schwarzenbergk	4990
199	Roman Sklenák	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	RSklenak	3121279067	953	FALSE	FALSE	2015-03-27 13:14:05+00:00	RSklenak	113
200	Bohuslav Sobotka	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	BohuslavSobotka	62798772	902	FALSE	FALSE	2009-08-04 12:03:38+00:00	BohuslavSobotka	0

201	Olga Sommerová	TOP 9.00	LES	0	1	1	6.6666665	7.4074073	OlgaSommerka	2692512530	67	FALSE	FALSE	2014-07-30 10:59:12+00:00	OlgaSommerka	26
202	Antonín Staněk	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	StanekAntonin	789389261287985152	1242	FALSE	FALSE	2016-10-21 08:54:00+00:00	StanekAntonin	630
203	Martin Stropnický	ANO	ANO	0	1	1	4.4814816	4.6923075	stropnickym	3028101299	14344	FALSE	FALSE	2015-02-10 12:54:29+00:00	stropnickym	1200
204	Dan Ťok	ANO	BEZPP	0	1	1	4.4814816	4.6923075	tok5934	3619444823	2309	FALSE	TRUE	2015-09-11 10:35:32+00:00	tok5934	721
205	Petr Třešňák	Piráti	Piráti	0	1	1	6.1153846	4.2800002	petr_tresnak	1148241029038055427	939	FALSE	FALSE	2019-07-08 14:42:49+00:00	petr_tresnak	343
206	Kateřina Valachová	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	katavalachova	3308964299	7785	FALSE	FALSE	2015-06-05 05:18:22+00:00	katavalachova	2755
207	Jiří Valenta	KSČM	KSČM	0	1	1	2.3703704	1.1481482	JiValenta	335251072	95	FALSE	FALSE	2011-07-14 11:46:39+00:00	JiValenta	176
208	Jiří Ventruba	ODS	ODS	0	1	1	3.7777777	7.7777777	jiriventruba	733716534938480641	22	FALSE	FALSE	2016-05-20 17:50:28+00:00	jiriventruba	6
209	Ondřej Veselý	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	veselyposlanec	490759905	577	FALSE	FALSE	2012-02-12 21:51:58+00:00	veselyposlanec	592
210	Adam Vojtěch	ANO	BEZPP	0	1	1	4.4814816	4.6923075	adamvojtechano	931157413331337216	89173	FALSE	TRUE	2017-11-16 13:50:02+00:00	adamvojtechano	2774
211	Lubomír Volný	SPD	SPD	0	1	1	1.4814814	8.8461542	lubomir_volny	930746503701909504	6710	FALSE	FALSE	2017-11-15 10:37:13+00:00	lubomir_volny	26203
212	Václav Votava	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	VotavaVaclav	3143259652	923	FALSE	FALSE	2015-04-07 09:14:01+00:00	VotavaVaclav	2915
213	Veronika Vrecionová	ODS	ODS	0	1	1	3.7777777	7.7777777	vrecionova	953628973551976448	1826	FALSE	FALSE	2018-01-17 14:03:59+00:00	vrecionova	1190
214	Tomáš Vymazal	Piráti	Piráti	0	1	1	6.1153846	4.2800002	tom_vymazal	542141739	1156	FALSE	FALSE	2012-03-31 23:10:30+00:00	tom_vymazal	982
215	Rostislav Vyzula	ANO	ANO	0	1	1	4.4814816	4.6923075	RostislavVyzula	740543211060506625	471	TRUE	FALSE	2016-06-08 13:57:14+00:00	RostislavVyzula	653
216	Jan Zahradník	ODS	ODS	0	1	1	3.7777777	7.7777777	janzahradnik_jc	719514068294451202	961	FALSE	FALSE	2016-04-11 13:14:56+00:00	janzahradnik_jc	691
217	Lubomír Zaorálek	ČSSD	ČSSD	0	1	1	5.7407408	2.7407408	ZaoralekL	2776167217	38117	FALSE	FALSE	2014-08-28 09:58:43+00:00	ZaoralekL	4653
218	Radek Zlesák	ANO	ANO	0	1	1	4.4814816	4.6923075	RZlesak	1310912933833170944	5	FALSE	FALSE	2020-09-29 12:03:15+00:00	RZlesak	0

B.2 Politicians without Twitter

	Jméno	Kandidátka	Navrhující strana	Politická příslušnost	year	in_2021	has_twitter	nickname	account_id	in_2017
0	Ivan Adamec	SPOLU	ODS	ODS	2021	1	0	0	99999999999	0
3	Andrea Babišová	ANO	ANO	ANO	2021	1	0	0	99999999999	0
5	Jana Bačíková	SPOLU	ODS	ODS	2021	1	0	0	99999999999	0
6	Vladimír Balaš	Piráti+STAN	STAN	STAN	2021	1	0	0	99999999999	0
7	Margita Balaštíková	ANO	ANO	ANO	2021	1	88	0	99999999999	0
10	Jaroslav Bašta	SPD	SPD	SPD	2021	1	0	0	99999999999	0
17	Roman Bělor	Piráti+STAN	STAN	STAN	2021	1	0	0	99999999999	0
23	Stanislav Berkovec	ANO	ANO	ANO	2021	1	0	0	99999999999	0
28	Milan Brázdil	ANO	ANO	ANO	2021	1	0	0	99999999999	0
35	Oldřich Černý	SPD	SPD	SPD	2021	1	0	0	99999999999	0
40	Aleš Dufek	SPOLU	KDU-ČSL	KDU-ČSL	2021	1	0	0	99999999999	0
41	Jaroslav Dvořák	SPD	SPD	SPD	2021	1	0	0	99999999999	0
43	Jaroslav Faltýnek	ANO	ANO	ANO	2021	1	0	0	99999999999	0
44	Kamal Farhan	ANO	ANO	ANO	2021	1	0	0	99999999999	0
49	Eva Fialová	ANO	ANO	ANO	2021	1	0	0	99999999999	0
54	Stanislav Fridrich	ANO	ANO	BEZPP	2021	1	0	0	99999999999	0
58	Jiří Hájek	Piráti+STAN	STAN	STAN	2021	1	0	0	99999999999	0
60	Jana Hanzlíková	ANO	ANO	ANO	2021	1	0	0	99999999999	0
64	Tomáš Helebrant	ANO	ANO	ANO	2021	1	0	0	99999999999	0
67	Jan Hofmann	SPOLU	ODS	ODS	2021	1	0	0	99999999999	0
70	Jan Hrnčíř	SPD	SPD	SPD	2021	1	0	0	99999999999	0
71	Ivan Jáč	ANO	ANO	BEZPP	2021	1	0	0	99999999999	0
74	Miloslav Janulík	ANO	ANO	ANO	2021	1	0	0	99999999999	0
79	David Kasal	ANO	ANO	ANO	2021	1	0	0	99999999999	0
83	Lenka Knechtová	ANO	ANO	ANO	2021	1	0	0	99999999999	0
84	Jiří Kobza	SPD	SPD	SPD	2021	1	88	0	99999999999	0
87	Tomáš Kohoutek	ANO	ANO	ANO	2021	1	0	0	99999999999	0
91	Josef Kott	ANO	ANO	ANO	2021	1	0	0	99999999999	0
98	Jan Kubík	ANO	ANO	ANO	2021	1	0	0	99999999999	0
104	Hubert Lang	ANO	ANO	ANO	2021	1	0	0	99999999999	0
106	Vladimíra Lesenská	SPD	SPD	SPD	2021	1	0	0	99999999999	0
108	Jarmila Levko	Piráti+STAN	STAN	SLK	2021	1	0	0	99999999999	0
110	Petr Liška	Piráti+STAN	STAN	STAN	2021	1	0	0	99999999999	0
128	Miloš Nový	SPOLU	TOP 9.00	TOP 9.00	2021	1	0	0	99999999999	0
135	Renata Oulehlová	ANO	ANO	ANO	2021	1	0	0	99999999999	0
136	Zuzana Ožanová	ANO	ANO	ANO	2021	1	0	0	99999999999	0
139	Berenika Peštová	ANO	ANO	ANO	2021	1	0	0	99999999999	0
140	František Petrtýl	ANO	ANO	ANO	2021	1	0	0	99999999999	0
144	Marie Pošarová	SPD	SPD	SPD	2021	1	0	0	99999999999	0
145	Lucie Potůčková	Piráti+STAN	STAN	STAN	2021	1	0	0	99999999999	0
147	Petra Quittová	Piráti+STAN	STAN	STAN	2021	1	0	0	99999999999	0

147	Petra Quittová	Piráti+STAN	STAN	STAN	2021	1	0	0	99999999999	0
151	Michal Ratiborský	ANO	ANO	ANO	2021	1	0	0	99999999999	0
152	Jan Richter	ANO	ANO	ANO	2021	1	88	0	99999999999	0
156	Drahoslav Ryba	ANO	ANO	BEZPP	2021	1	0	0	99999999999	0
158	Rudolf Salvetr	SPOLU	ODS	ODS	2021	1	0	0	99999999999	0
160	Jan Síla	SPD	SPD	SPD	2021	1	0	0	99999999999	0
162	Karel Sládeček	SPD	SPD	SPD	2021	1	88	0	99999999999	0
163	Jiří Slavík	SPOLU	TOP 9.00	TOP 9.00	2021	1	0	0	99999999999	0
167	Jiří Strýček	ANO	ANO	ANO	2021	1	88	0	99999999999	0
172	Michaela Šebelová	Piráti+STAN	STAN	STAN	2021	1	0	0	99999999999	0
175	Iveta Štefanová	SPD	SPD	SPD	2021	1	0	0	99999999999	0
180	Libor Turek	SPOLU	ODS	ODS	2021	1	0	0	99999999999	0
189	Vít Vomáčka	SPOLU	ODS	BEZPP	2021	1	0	0	99999999999	0
192	Petr Vrána	ANO	ANO	ANO	2021	1	88	0	99999999999	0
194	Lubomír Wenzl	ANO	ANO	ANO	2021	1	0	0	99999999999	0
195	Milan Wenzl	ANO	ANO	BEZPP	2021	1	0	0	99999999999	0
198	Vladimír Zlínský	SPD	SPD	SPD	2021	1	0	0	99999999999	0
2	Hana Aulická Jírovcová		KSČM	KSČM	2017	0	0	0	99999999999	1
13	Jiří Běhounek		ČSSD	BEZPP	2017	0	0	0	99999999999	1
25	Irena Blažková		ANO	ANO	2017	0	88	0	99999999999	1
26	Marian Bojko		SPD	SPD	2017	0	0	0	99999999999	1
29	Andrea Brzobohatá		ANO	BEZPP	2017	0	0	0	99999999999	1
33	Alexander Černý		KSČM	KSČM	2017	0	0	0	99999999999	1
34	Monika Červíčková		ANO	ANO	2017	0	0	0	99999999999	1
57	Miroslav Grebeníček		KSČM	KSČM	2017	0	0	0	99999999999	1
58	Stanislav Grospič		KSČM	KSČM	2017	0	0	0	99999999999	1
62	Jiří Hlavatý		ANO	BEZPP	2017	0	0	0	99999999999	1
70	Jan Chvojka		ČSSD	ČSSD	2017	0	0	0	99999999999	1
75	Monika Jarošová		SPD	SPD	2017	0	0	0	99999999999	1
81	Pavel Juříček		ANO	ANO	2017	0	0	0	99999999999	1
82	Iva Kalátová		ANO	ANO	2017	0	0	0	99999999999	1
89	Jiří Kohoutek		SPD	SPD	2017	0	0	0	99999999999	1
93	Vladimír Koníček		KSČM	KSČM	2017	0	0	0	99999999999	1
98	Pavel Kováčik		KSČM	KSČM	2017	0	0	0	99999999999	1
109	Jana Levová		SPD	SPD	2017	0	0	0	99999999999	1
111	Leo Luzar		KSČM	KSČM	2017	0	88	0	99999999999	1
116	Jaroslav Martinů		ODS	ODS	2017	0	0	0	99999999999	1
119	Květa Matušovská		KSČM	KSČM	2017	0	0	0	99999999999	1
120	Eva Matyášová		ANO	ANO	2017	0	0	0	99999999999	1
121	Ilona Mauritzová		ODS	BEZPP	2017	0	0	0	99999999999	1
128	František Navrka		Piráti	Piráti	2017	0	0	0	99999999999	1
130	Ivana Nevludová		SPD	SPD	2017	0	0	0	99999999999	1
136	Zdeněk Ondráček		KSČM	KSČM	2017	0	0	0	99999999999	1
136	Zdeněk Ondráček		KSČM	KSČM	2017	0	0	0	99999999999	1
139	Petr Pávek		STAN	SLK	2017	0	0	0	99999999999	1
140	Daniel Pawlas		KSČM	KSČM	2017	0	0	0	99999999999	1
144	Marie Pěnčíková		KSČM	KSČM	2017	0	0	0	99999999999	1
146	Vojtěch Pikal		Piráti	Piráti	2017	0	0	0	99999999999	1
147	Pavel Plzák		ANO	ANO	2017	0	0	0	99999999999	1
148	Zdeněk Podal		SPD	SPD	2017	0	0	0	99999999999	1
156	Věra Procházková		ANO	ANO	2017	0	0	0	99999999999	1
157	Jaroslava Puntová		ANO	ANO	2017	0	0	0	99999999999	1
167	Miloslava Rutová		ANO	ANO	2017	0	0	0	99999999999	1
171	Miroslav Samaš		ANO	ANO	2017	0	0	0	99999999999	1
172	Jan Schiller		ANO	ANO	2017	0	0	0	99999999999	1
185	Pavel Šindelář		ODS	ODS	2017	0	0	0	99999999999	1
186	Karla Šlechtová		ANO	BEZPP	2017	0	0	0	99999999999	1
187	Lubomír Španěl		SPD	SPD	2017	0	0	0	99999999999	1
193	Lukáš Vágner		ČSSD	ČSSD	2017	0	0	0	99999999999	1
194	František Vácha		TOP 9.00	BEZPP	2017	0	0	0	99999999999	1
199	Petr Venhoda		ANO	ANO	2017	0	0	0	99999999999	1
209	Miloslava Vostrá		KSČM	KSČM	2017	0	0	0	99999999999	1
214	Jaroslav Vymazal		ODS	ODS	2017	0	0	0	99999999999	1

C Sentiment Analysis

C.1 Example of Translated Aata

translated_text	targeting_tweet_text_cleaned_EN
prdel čuráka před zácpou	ass dick before constipation
prý Ukrajinci kradou znásilnují ženy ČR, natom pravdy!	it is said that Ukrainians steal women from the Czech Republic, but the truth!
Skvjelý lydi	Skvjelý lydi
Čau 25085 Bureši	Hi 25085 Sails
Dnes významný proto třeba zopakovat učivo základní školy:	Today, therefore, it is important to repeat the curriculum of primary school:
Pěkný, konečně autentický video Předsedou.	Nice, finally authentic video by the President.
Milé samozivitelky maminky budoucnost vaše vašich dětí:	Dear single mothers, the future of your children:
Kdyby zcela náhodou někdo chtěl vědět kdo stojí inflací, tak musí položit otázku : Haló Haló tady nesmysl covid. víte tištěni nepodlozenyc	If, by any chance, someone wants to know who is in charge of inflation, they have to ask the question: Hello Hello, nonsense covid h
Česká národní banka neutrhla řetězu. ČNB praktická. Oni tam věděli už dávno. Nebudu psát jistých věcech. Nicméně třeba pochválit ČNE	The Czech National Bank did not break the chain. CNB practical. They knew there a long time ago. I will not write certain things. How
neutral	neutral
Odporný estébácko bolševický gaunere Bureši už ZMIZ Husákovy normalizace!!!	The disgusting Bolshevik gauner Bureši has disappeared Husák's normalization !!!
Zapomněl jsem elektrické automobily, letadla atd . Hold zbraně hovadiny vždycky. rozvoj nejsou peníze.	I forgot electric cars, planes, etc. Hold guns bullshit always. development is not money.
Velká pravda pana Wericha: Hloupost fackovanim nedá vyléčit ... Vzpomínám 4 hodinu raní Průhonice. Kaslal jste rozvoj země kaslal jste r	Mr. Werich's great truth: Stupidity by slapping cannot be cured ... I remember 4 hours early in Průhonice. You coughed up the develo
já Vás vůbec nechápu. Vždyť jste jasně měli ty inovace .Ty miliardy miliardy. už republika musí mít vyřešené elektrámy, teplárny, hnojiva ze	I don't understand you at all. You clearly had those innovations. Billions of billions. the republic must already have resolved power pl
Andyš zloděj	Andyš the thief
vláda wemen neví bohuzel! aspoň kvůli válce ukrajincum zmizela pandemie nemusí nosit nikde slintaky!	The government of Wemen does not know unfortunately! at least because of the war ukrinincum disappeared pandemic does not ha
řepkový magore! Zase všude zase smrdí otravuje občany ČR! Hlavně benzín stojí Whisky!	canola bullshit! It stinks again everywhere, it annoys the citizens of the Czech Republic! Mainly gasoline costs Whiskey!
vůbec gaunerem Válkem! káže vodu sám chlastá víno! Teď zese změnu spáchal nehorázný přestupek jezdí autě bez pásů! Dali dýchnou st	a rogue war at all! preaches water himself drinking wine! Now the change has been committed by a heinous offense of driving a car w
Kde máme svobodu demokracii? Už nikdo jiný volby nevyhraje.	Where do we have freedom democracy? No one else will win the election.
hovno! EU nás vyžírá, zneužívá, přikazuje aby jme nebyli soběstační! Udělali ČR odpad!	shit! The EU is devouring us, abusing us, ordering us not to be self-sufficient! They made the Czech Republic a waste!
Bureši, Ty Slovenské prolhané trestně stíhané bolševické estébácké zlodějské HOVADO už ZMIZ mého Česka!!!	Bureš, You Slovak lying prosecuted Bolshevik estébácké thief HOVADO is already disappearing my Czech Republic !!!
Bureši, Ty estébácko bolševický gaunere gaunerská podvodnická trestně stíhaná zlodějská prolhaná už svých prasárnách Česku ZMIZ sm	Bureši, Ty estébácko bolševický gaunere gauner cheating criminal prosecuted thief lying already in his pigsty Czech Republic ZMIZ s
Estébácké Slovenské prolhané trestně stíhané HOVADO Bureši už ZMIZ!!! Gaunere gaunerská!!! Jsi prostě Slovenská žumpa, příšerným s	Estébácké Slovenské lie lying prosecuted HOVADO Bureši DISAPPEAR !!! Gaunere gaunerská !!! You are simply a Slovak cesspool, a
zase žranice! Zlatá lepenova!	again žranice! Gold cardboard!
asi tak	I guess
už zase rozhazuji prachy našich daní nové neprustrelne auta! Asi ty podvodníci nemají čisté svědomí že!	I'm wasting our taxes on new bulletproof cars! I guess those crooks don't have a clear conscience!
Ukrajinští nacionalisté pořádají polovojenské tábory. kalašnikovy tam zacházejí osmileté děti. Během zvláštních polovojenských táborů po	Ukrainian nationalists hold paramilitary camps. The Kalashnikovs are treated there by eight-year-olds. During special paramilitary car
jsou žumpy světa.	are the cesspools of the world.
Nejsi náš přítel. Jsi prolhanej zloděj. Táhni estébáku Bureši	You are not our friend. You are a lying thief. Pull Esther, Bures
právě proto již konce roku prý bude postaveno alespoň 500 000 domků zahrádkou sliboval Havel.	that is why at the end of the year it is said that at least 500,000 houses will be built in the garden promised by Havel.
Vždyť přeci není tvoje pumpa, kokote	It's not your pump, cock
Zloději, víš některé pumpy zlevnily ?	Thieves, do you know some pumps have become cheaper?
jurecka zemědělský analfabet. Vysinuty bez prakce!	jurecka agricultural illiterate. Exhausted without action!
dostane bidena odměnu podporuje válku zbraněmi!	gets a bounty reward supports war weapons!
mají kde porodit? jesle, školky, sunar, pliny atd!	have a place to give birth? nursery, kindergarten, sunar, pliny etc!
Hnusný estébák 25085 dotační podvodník zloděj	Disgusting estébák 25085 grant cheater thief
Máme porodnic, jesli, školek?	Do we have maternity hospitals, nurseries, kindergartens?
KRIPLE	KRIPLE

Figure 7: Original Text in Czech and Translated Text

C.2 Comparison of Original and Extended Lexicon

	sentiment	count_sent_no_improve	count_sent_improved
0	Negative	3930	4204
1	Neutral	3177	2983
2	Positive	2449	2369

Figure 8: Sentiment Category, Original and Extended Lexicon

D Figures

D.1 Comparison of Original and Log Measures

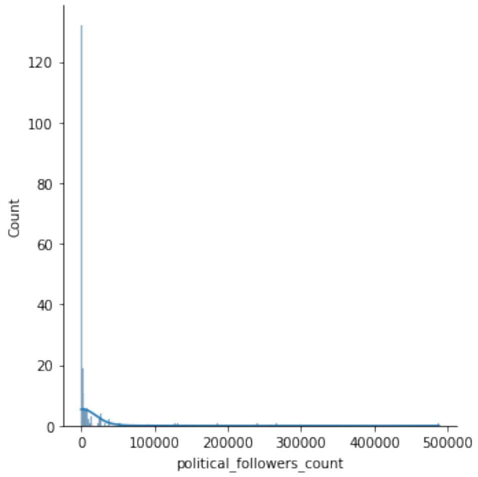


Figure 9: Count of Political Account Followers

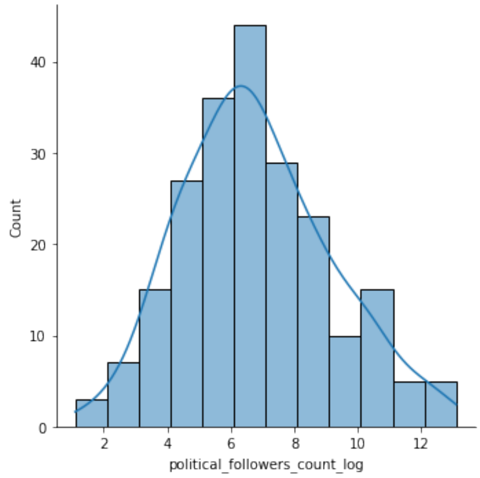


Figure 10: Count of Political Account Followers Log

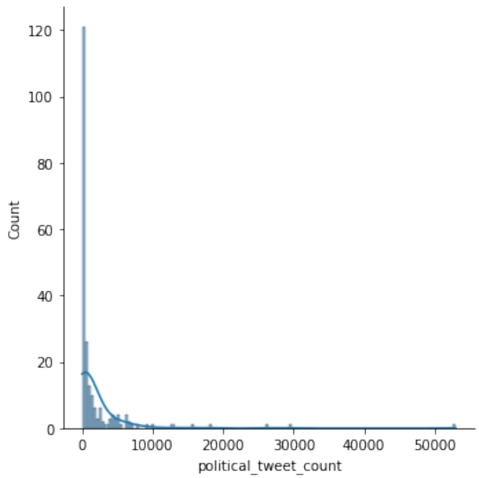


Figure 11: Count of Political Account Tweets

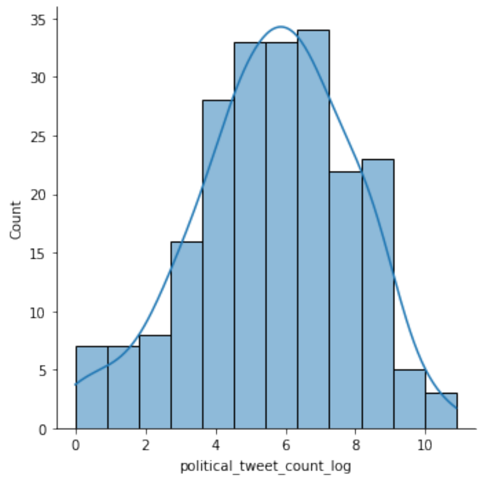


Figure 12: Count of Political Account Tweets log

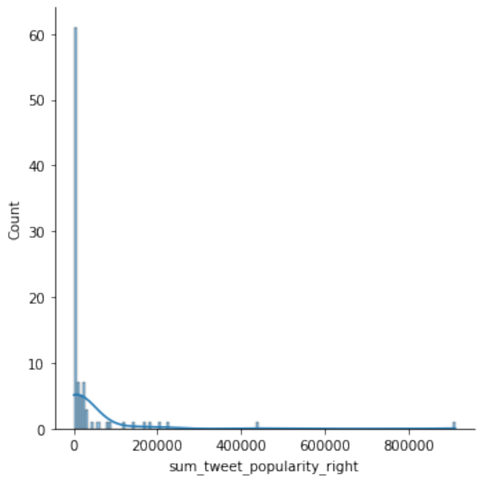


Figure 13: Political tweet popularity responded by right wing trolls

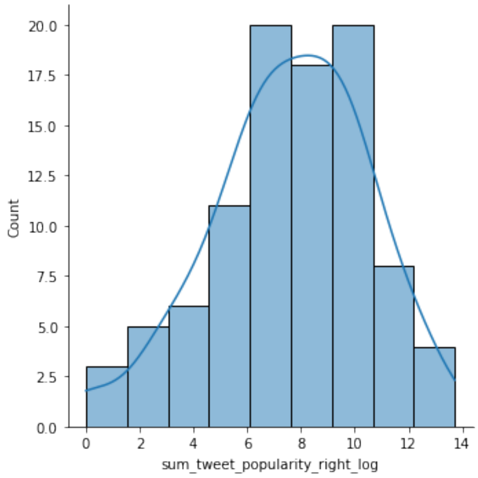


Figure 14: Log of political tweet popularity responded by right wing trolls

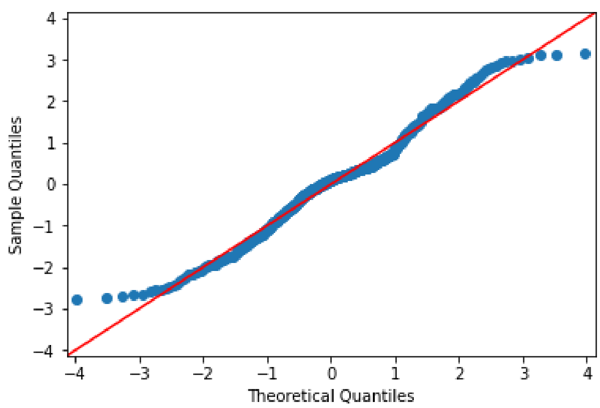
E Results: Less Aggregated Data

E.1 DV: Sentiment of Tweet Produced by Troll

Dep. Variable:	Sentiment Score	**R-squared:**	0.031
Model:	OLS	**Adj. R-squared:**	0.021
Method:	Least Squares	**F-statistic:**	3.178
Date:	Mon, 06 Jun 2022	**Prob (F-statistic):**	0.00446
Time:	23:42:48	**Log-Likelihood:**	-231.51
No. Observations:	606	**AIC:**	477.0
Df Residuals:	599	**BIC:**	507.9
Df Model:	6		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-0.3735	0.157	-2.374	0.018	-0.682	-0.065
Troll Ideo Binary)[T.right]	0.0925	0.139	0.667	0.505	-0.180	0.365
Politician Ideology	0.0139	0.022	0.642	0.521	-0.029	0.056
Troll Ideo Binary)[T.right]:Politician Ideology	-0.0050	0.024	-0.214	0.831	-0.051	0.041
Politician Followers Log	0.0123	0.010	1.238	0.216	-0.007	0.032
Politician All Tweets Log	0.0170	0.014	1.211	0.226	-0.011	0.045
Politician Tweet Popularity Log	-0.0147	0.005	-2.886	0.004	-0.025	-0.005

Table 4: Results: OLS Model for DV - Sentiment of Troll Tweet on Least Aggregated Data

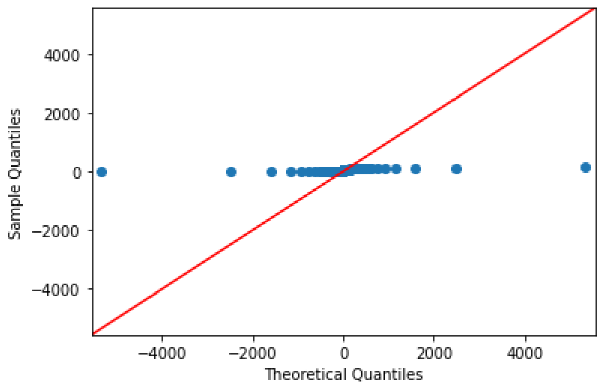


E.2 DV: Number of Targeting Tweets Produced by Troll, First Step - Binomial

Dep. Variable:	targeted	**No. Observations:**	8108
Model:	GLM	**Df Residuals:**	8102
Model Family:	Binomial	**Df Model:**	5
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1651.3
Date:	Tue, 07 Jun 2022	**Deviance:**	3302.6
Time:	19:00:52	**Pearson chi2:**	6.02e+03
No. Iterations:	7	**Pseudo R-squ. (CS):**	0.1167
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-6.6909	0.440	-15.218	0.000	-7.553	-5.829
Troll Ideo Binary)[T.right]	-1.8522	0.417	-4.445	0.000	-2.669	-1.035
Political Ideology	-0.0845	0.064	-1.324	0.185	-0.210	0.041
Troll Ideo Binary)[T.right]:Political Ideology	0.1977	0.070	2.831	0.005	0.061	0.335
Politician Followers Log	0.4305	0.031	13.999	0.000	0.370	0.491
Politician All Tweets Log	0.2485	0.042	5.948	0.000	0.167	0.330

Table 5: Results: Binomial Model for DV - Target (or Not) Least Aggregated Data

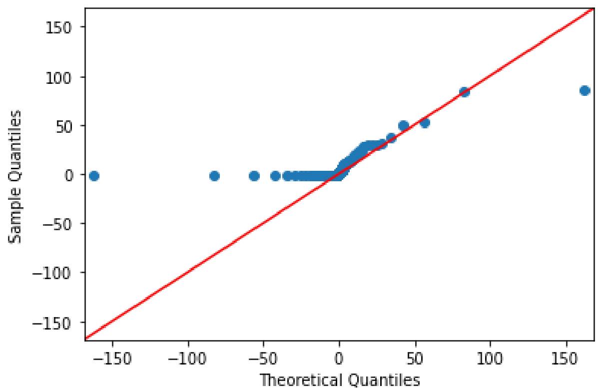


E.3 DV: Number of Targeting Tweets Produced by Troll, Second Stage - Negative Binomial

Dep. Variable:	Sum Tweets Troll Targeted	**No. Observations:**	606
Model:	GLM	**Df Residuals:**	600
Model Family:	NegativeBinomial	**Df Model:**	5
Link Function:	Log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-1685.8
Date:	Tue, 07 Jun 2022	**Deviance:**	736.47
Time:	19:04:58	**Pearson chi2:**	1.95e+03
No. Iterations:	11	**Pseudo R-squ. (CS):**	0.3012
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-0.6316	0.490	-1.288	0.198	-1.593	0.329
Troll Ideo Binary)[T.right]	-2.4047	0.423	-5.681	0.000	-3.234	-1.575
Political Ideology	-0.2202	0.066	-3.333	0.001	-0.350	-0.091
Troll Ideo Binary)[T.right]:Political Ideology	0.3363	0.072	4.645	0.000	0.194	0.478
Politician Followers Log	0.2147	0.030	7.071	0.000	0.155	0.274
Politician All Tweets Log	0.2312	0.044	5.233	0.000	0.145	0.318

Table 6: Results: Negative Binomial Model for DV - Sum of Troll Least Aggregated Data



F Results: Aggregated Data

F.1 DV: Frequency of Targeting Tweets by Right-wing Trolls, OLS Model

Dep. Variable:	Sum Tweets Right Trolls	**R-squared:**	0.583
Model:	OLS	**Adj. R-squared:**	0.573
Method:	Least Squares	**F-statistic:**	59.59
Date:	Tue, 07 Jun 2022	**Prob (F-statistic):**	1.29e-38
Time:	23:16:15	**Log-Likelihood:**	-1053.3
No. Observations:	219	**AIC:**	2119.
Df Residuals:	213	**BIC:**	2139.
Df Model:	5		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	-28.9114	9.604	-3.010	0.003	-47.842	-9.981
Political Ideology	2.5074	1.184	2.118	0.035	0.174	4.841
Sum Tweets Left Trolls	-0.4919	0.100	-4.924	0.000	-0.689	-0.295
Sum Tweets Unknown Ideo Trolls	0.4283	0.035	12.356	0.000	0.360	0.497
Politician Followers Log	1.0314	1.610	0.641	0.522	-2.142	4.204
Politician All Tweets Log	2.3654	1.590	1.488	0.138	-0.769	5.499

Omnibus:	290.022	**Durbin-Watson:**	1.959
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	30348.370
Skew:	5.575	**Prob(JB):**	0.00
Kurtosis:	59.582	**Cond. No.**	480.

Table 7: Results: OLS Model Aggregated Data

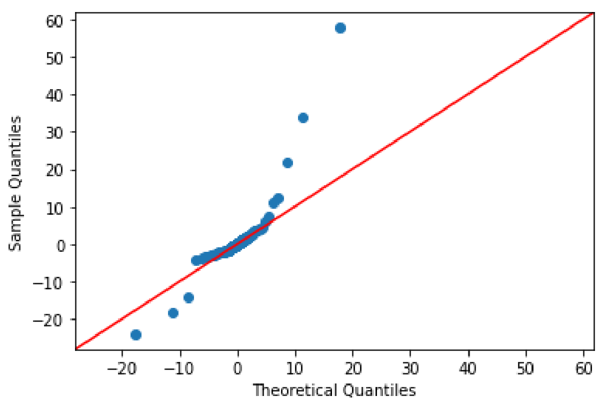


Figure 15: Residuals for OLS Model on Aggregated Data

F.2 DV: Frequency of Targeting Tweets by Right-wing Trolls, Simple Negative Binomial Model

Dep. Variable:	Sum Tweets Right Trolls	**No. Observations:**	219
Model:	GLM	**Df Residuals:**	213
Model Family:	NegativeBinomial	**Df Model:**	5
Link Function:	Log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-422.83
Date:	Tue, 07 Jun 2022	**Deviance:**	240.05
Time:	23:31:56	**Pearson chi2:**	214.
No. Iterations:	18	**Pseudo R-squ. (CS):**	0.9661
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P> |z|**	**[0.025**	**0.975]**
Intercept	-7.7240	0.585	-13.202	0.000	-8.871	-6.577
Political Ideology	0.2443	0.054	4.556	0.000	0.139	0.349
Sum Tweets Left Trolls	-0.0004	0.003	-0.125	0.900	-0.007	0.006
Sum Tweets Unknown Ideo Trolls	0.0032	0.001	2.629	0.009	0.001	0.006
Politician Followers Log	0.5289	0.073	7.236	0.000	0.386	0.672
Politician All Tweets Log	0.5115	0.084	6.094	0.000	0.347	0.676

Table 8: Results: Simple Negative Binomial Model on Aggregated Data

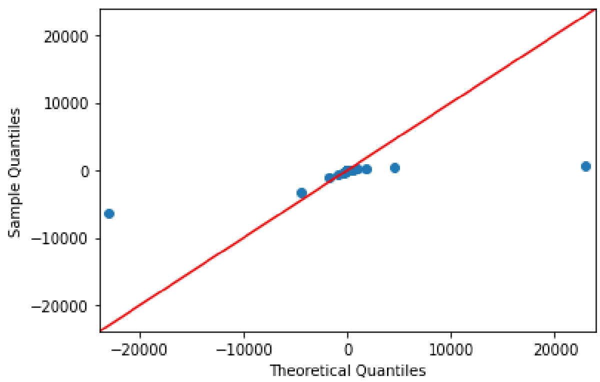


Figure 16: Residuals for Simple Negative Binomial Model on Aggregated Data

G Residuals

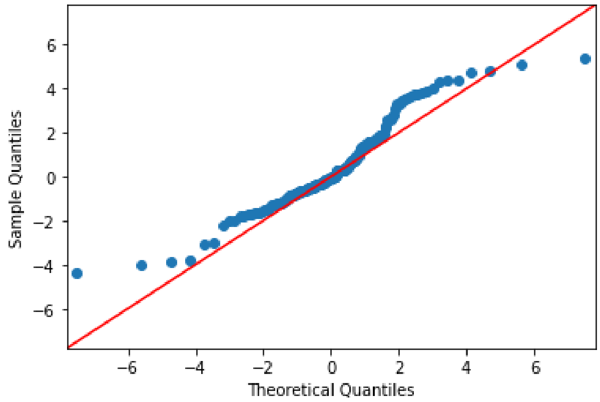


Figure 17: Residuals for First Stage Binomial Model on Aggregated Data

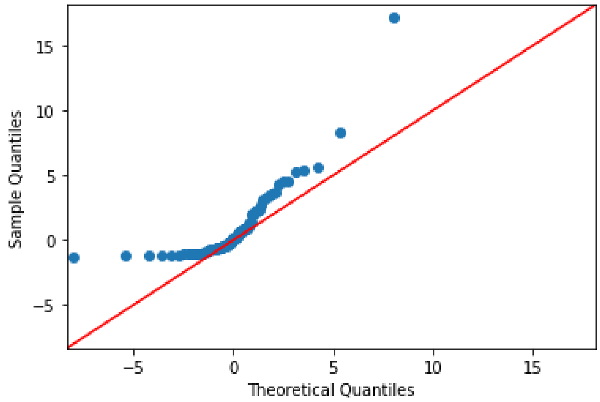


Figure 18: Residuals for Second Stage Negative Binomial Model on Aggregated Data

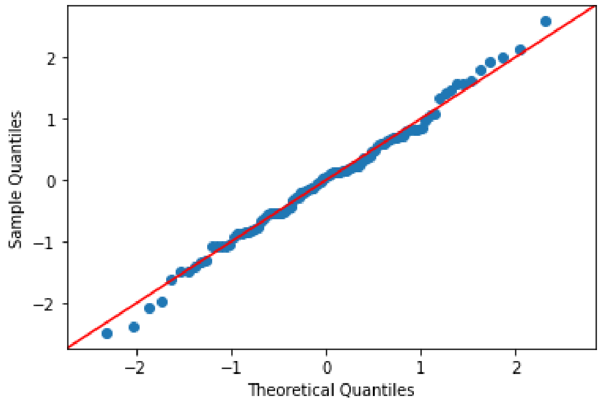


Figure 19: Residuals for OLS Model Aggregated Data