# The Internet, Social Media, and Elite Extremeness: Evidence from Chile

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**Abstract**

The Internet and social media have significantly affected democracies around the world. Yet, little is known about their direct impact on political elites. This article posits that the expansion of the internet and social media has increased elite ideological extremeness through two channels: a) access to the internet increases voter radicalism, affecting politicians who respond to their constituencies and b) users reward extreme politicians on social media. I test these hypotheses in Chile, using spatial variation on 3G mobile internet, sentiment analysis of Facebook posts, roll-call voting data, and public opinion polls. I find that politicians have increased their Facebook activity according to the geographical variation of access to 3G mobile internet. As a result, they have moved to more ideologically extreme positions. Exploration of mechanisms confirms that elite extremeness is rewarded on social media, as negative posts made by extreme politicians receive far more engagement. Likewise, there is no evidence that elite extremeness is explained by an increase in voters' radicalism.

***Keywords***— 3G Mobile Internet, social media, elite extremism, Chile

# Introduction

The impact of the internet and social media on representative democracy has been extensively discussed. The optimistic perspective is that political discussions through social media enhance democratic accountability, providing citizens with unprecedented opportunities to voice their concerns and hold the powerful accountable.[1] However, recent events have called into question this perspective. A grimmer narrative has dominated public debates after the 2016 United States presidential election and the Brexit referendum. Nowadays, social media are deemed responsible for political polarization, acting as ideological "echo chambers" and, more generally, enabling overly aggressive and simplistic political discussions.

The academic literature in this area has heavily focused on voters, finding, for example, that information transmitted through social media affects voter turnout (Bond et al., 2012), democratic accountability (Enriquez et al., 2022; Garbiras-Díaz and Montenegro, 2022), protests against autocratic regimes (Enikolopov et al., 2020; Steinert-Threlkeld, 2017), polarization (Allcott et al., 2020), violence (Bursztyn et al., 2019), and the spread of false news (Guess et al., 2020). However, with a few notable exceptions (e.g. Barberá et al., 2019; Bessone et al., 2019), little empirical research has been conducted on the relationship between the internet, social media, and political elites. In this sense, it is unclear whether politicians pay attention to social media and whether they alter their behavior due to this exposure.

In what sense can the Internet and social media affect political elites? In this paper, I argue that the expansion of internet access and the penetration of social media in politics increases *ideological extremeness* among political elites through two non-mutually exclusive mechanisms.

On the one hand, access to the internet can increase voter polarization and distrust of government among the public (Guriev et al., 2021; Melnikov, 2021), which could be reflected in the way that users communicate on social media. As politicians respond to an increasing portion of their constituencies, they, in turn, might acquire more extreme positions. I denominate this the *extrinsic* channel, as the impact of social media on elites is a manifestation of a societal trend

[1] See https://www.intelligencesquaredus.org/debates/social-media-good-democracy

towards extremism, which is expressed on social media. On the other, users may reward extremeness on social media, allowing negative messages to receive greater engagement. Previous research suggests that frequent commentators on social media are politicized, have polarized opinions, use toxic language, and reward extreme politicians (Kim et al., 2021; Hong and Kim, 2016). Moreover, the digital world is also characterized by ideological segregation (Bakshy et al., 2015) and a high presence of false news (Guess et al., 2019). Thus, politicians who are constantly exposed to this environment may be afraid of bad publicity on social media regarding their offline behavior, leading them to move to extreme positions. I call this the *intrinsic* mechanism, as the potential effect of social media on elite extremism is explained by politicians who may be excessively responsive to their online audience, even if such voters do not represent a significant fraction of voters.

In this article, I examine the relationship between access to the internet, social media consumption, and elite extremeness in Chile during the 2010-2020 period. The Chilean case is an intriguing one for addressing these research goals. Besides the variation in access to the internet and Facebook activity among politicians in the last decade, the political context has interesting characteristics. Chileans have exhibited an increasing distrust of traditional institutions, including the traditional media, namely TV and print newspapers. However, the opposite trend applies to social media. Indeed, an increasing number of Chileans seem to trust more in social media (Facebook and Twitter) than in other outlets, which is probably reflected in the growing number of citizens who use these platforms to consume political news. Thus, social media have become one of the main sources of political information (see the section Chilean Context for descriptive evidence).

To test my argument, I conduct three types of analyses. In the first place, I examine whether Chilean members of the Chamber of Deputies[2] pay more attention to Facebook when an increasing share of their constituencies has access to 3G mobile internet.[3] Empirically, I estimate a two-way fixed effect model, regressing measures of Facebook activity - likes, shares, and total interactions -

[2]I decided to use deputies instead of senators for two reasons. First, there are a greater number of deputies, allowing for more statistical traction. Second, senators are more nationally-oriented figures elected in larger electoral districts, so it would be unlikely to expect responsiveness to local-level variation in access to the internet. I could not use both because senators and deputies do not share the same districts.

[3]I decided to use Facebook data as opposed to other platforms such as Twitter because the former has much higher penetration among the public (see Figure A1. Moreover, Twitter is the space for national discussions whereas on Facebook, politicians interact more with voters from their constituencies

on 3G mobile internet coverage using a panel data of Chilean legislators. Here, I found a substantive effect of 3G mobile internet on Facebook activity among politicians, implying that when citizens have more access to the internet, legislators spend much more time interacting on Facebook.

Second, I analyze if either district-level access to the internet or large levels of Facebook activity increases the level of ideological extremeness among political elites. The use of behavioral outcomes outside the digital world is crucial to understanding the impact of social media on democracies, as such outcomes can have real-world consequences. In this article, I decided to use roll-call voting data from the Chilean congress, which allowed for a measure of ideological extremeness on the left-right scale to be obtained. I regressed the measure on several measures of Facebook activity and/or 3G coverage. In this analysis, I consistently found that higher levels of Facebook interactions increase ideological extremeness among Chilean politicians.

Finally, I explore the intrinsic and the extrinsic channels that may explain the effect of Facebook activity on extremeness. For the former, I use sentiment analysis in the universe of Facebook posts made by politicians in the mentioned period to analyze whether negative posts have a higher circulation than positive ones. Meanwhile, to explore the extrinsic channel, I utilize public opinion data, to see if voters in places with higher access to the internet also exhibit extreme political attitudes. The results suggest that extremeness is rewarded on social media, as negative posts, generally written by extreme politicians, receive many more reactions, and, consequently, achieve greater circulation. Additionally, there is no evidence that a societal trend toward extremism explains this effect. Consequently, the evidence is more consistent with the intrinsic mechanism, implying that the effect of social media on elite extremeness is likely explained by its internal dynamics rather than by a trend toward radicalism among voters.

This article contributes to the literature in three ways. First, my paper is one of the few that addresses how social media affect political elites in domains outside the digital world. Even though previous research has documented the large impact of the traditional media on politicians (e.g. Besley and Burgess, 2022; Stromberg, 2004; Eisensee and Stromberg, 2007; Snyder and Strömberg, 2010; Durante and Zhuravskaya, 2018; Raffler, 2019), the particularities of social media - instantaneous communication and higher levels of toxicity (Kim et al., 2021)– imply that the it can affects elites in different ways. As demonstrated in this paper, the internal dynamics of social media plausibly impact ideological extremeness, which may have concrete consequences for the tone of political discussion and for the capacity of the system to solve pressing issues through consensus. Second, my paper speaks to the old discussion about whether politicians lead or follow the public (Lenz, 2012), in this case, regarding extremism. The evidence suggests that an increase in extremism is not driven by a majority of voters; rather, I show that relatively few politicized and active social media users have the capacity to influence elites by capturing their attention and by constantly reacting to their messages. Third, my article contributes to the understanding of polarization and democratic backsliding in the global south. Indeed, in the last years, Latin American countries such as Colombia, Peru, Brazil, and Chile have experienced increasing levels of elite polarization, as evidenced by the type of candidates disputing the presidential elections. Social media penetration is a plausible driving force behind this phenomenon, as it encourages politicians to spend time chasing "likes," which, as I demonstrate, could have consequences for the functioning of democracy.

# The Media, Voters, and Politicians

An extensive body of scholarship in Political Science and Economics has established a connection between media presence and voters' outcomes, as the media have traditionally been considered a key source of information about public affairs. Scholars in the United States (US) have studied this topic by exploiting variations in the entry of traditional media, finding a positive impact of both newspaper and television on political participation and voter turnout (Gentzkow, 2006; Gentzkow et al., 2011; Schulhofer-Wohl and Garrido, 2013). Not surprisingly, these effects on voters are transposed onto politicians. Scholars suggest that media penetration induces politicians to pay attention to voters with higher media access, which is manifested in the disbursement of federal resources and in government responsiveness (Besley and Burgess, 2022; Stromberg, 2004; Eisensee and Stromberg, 2007; Snyder and Strömberg, 2010; Durante and Zhuravskaya, 2018; Raffler, 2019).

With the expansion of the internet, studies have also analyzed its effect on political behavior.

Social media have three key characteristics that make them different to traditional media: the *content* to which people are exposed, the *people* who participate in them, and the impact of the interactions that they generate between politicians and the public.

Regarding the content, scholars in the communication literature have focused on toxicity in political discussions, which has been defined as the expression of disrespect through the use of insulting language, profanity, or name calling. It can involve personal attacks and the employment of racist, sexist, or xenophobic expressions (Kim et al., 2021). Consistently, studies in this area have documented that toxic discourse is prevalent online (Sobieraj and Berry, 2011; Coe et al., 2014; Theocharis et al., 2016; Chen, 2017; Muddiman and Stroud, 2017; Oz et al., 2018; Ventura et al., 2021) and that it is higher than among offline political commentators (Kim et al., 2021).

Incivility in political discussions is closely related to false news. In this area, scholars have found that a significant portion of the electorate has been exposed to false news transmitted through social media and believed in its content (Allcott and Gentzkow, 2017), although the sources of fake news were extremely concentrated in a small proportion of users (Grinberg et al., 2019). Moreover, other scholars have documented that both Facebook and Twitter are the most important channels for diffusing such news (Guess et al., 2019).

Exposure to this new content affects other political outcomes. Indeed, a recent paper has explored the connection between the internet and attitudes toward democracy, finding that the internet increases non-civic attitudes. In a study covering 116 countries during the 2008-2017 period, Guriev et al. (2021) found that access to 3G internet increases skepticism toward democracy in various measures: confidence in government, the judicial system, elections, and government corruption. In the case of Europe, they also found that 3G favored anti-establishment populist opposition, typically the far right. In terms of mechanisms, the authors point out that 3G helps expose actual government corruption. In the US, Melnikov (2021) found that 3G internet increases the levels of polarization, which is consistent with evidence in a similar context (Allcott et al., 2020; Levy, 2021).

Studies have also explored the impact of internet content on more behavioral outcomes. For instance, scholars have found that the Internet decreases political participation in several western European countries (Falck et al., 2014; Campante et al., 2018; Gavazza et al., 2019), and increases the prevalence of violence and hate crimes (Bursztyn et al., 2019; Müller and Schwarz, 2021)

Other scholars have painted a more positive picture of the impact of social media. Studies have shown that precise information transmitted on social media can increase electoral accountability (Enriquez et al., 2022; Garbiras-Díaz and Montenegro, 2022), voter turnout, (Bond et al., 2012), political factual knowledge (Allcott et al., 2020), and protests against autocracies (Enikolopov et al., 2020; Steinert-Threlkeld, 2017).

Regarding the type of people who interact on social media, the evidence consistently shows that they markedly differ from the average citizen. Indeed, online commentators were found to have stronger partisan affiliations, consume more political news, discuss politics more frequently, vote more frequently, engage in other political activities more vigorously, and employ a more toxic language (Smith, 2014; Settle et al., 2016; Weeks et al., 2017). In this sense, as Kim et al. (2021) points out, there is a strong self-selection process for commenting and discussing politics on social media.

## Why should politicians be affected by social media?

In the previous section, it was established that there are high levels of toxicity among the political commentators on social media. Commentary is typically conducted by highly politicized people. If these facts are common knowledge, two questions remain: What is the impact of the interactions social media generate between politicians and the public?

The first answer relates to the possibility that a relatively large segment of the public engages with politicians on social media, demanding answers about different types of issues. This logic is addressed by Bessone et al. (2019), who uses differentials in access to 3G mobile coverage as a proxy for the number of voters with internet access that could potentially demand attention from their local politicians. They found that politicians become more active on social media in covered municipalities compared to non-covered ones. However, at the same time, they decreased their offline engagement places with higher 3G access, transferring fewer state resources to such areas. In this sense, even if the Internet induces politicians to spend time on social media, this is not translated into actual benefits for more widely covered areas.

Following this rationale, I state my first hypothesis, relating internet access to the amount of attention politicians pay to social media.

H1. Politicians whose district has greater access to 3G mobile internet should exhibit higher social media activity levels.

My second hypothesis refers to the impact of social media exposure to politicians' offline behavior. It is as follows:

H2. Chilean politicians with greater access to 3G mobile internet and high levels of social media activity should move towards more ideologically extreme positions.

I explore two reasons why social media exposure could increase elites' ideological extremeness. The first relates to the perceived electoral benefits that politicians may derive from following a relatively extreme set of voters. Indeed, if politicians have a significant online audience (probably partisan and relatively extreme), which represents an important portion of the actual voters, they may have incentives to move towards extreme positions, as they may be rewarded by these voters and, simultaneously, perceive that their offline audience, or the opposite party's core supporters, will not track their behavior as closely. This resembles the idea of strategic extremism developed by Glaeser et al. (2005), who claims that an increasing share of voters with extreme views could induce politicians to move to an extreme if politicians can convey information to core affiliates and hide it from the opposite party's core members. The assumptions of this model are realistic in the social media environment, as previous research has shown that, for example, Twitter users generally follow a higher share of ideologically congruent users (Bakshy et al., 2015; Barberá et al., 2015). Scholars in the United States have addressed the notion that partisan online audiences influence political elites. Indeed, Barberá et al. (2019) shows that legislators follow the issues discussed on social media, although only those prioritized by core supporters.

If this mechanism is true, then three conditions should hold true. First, the share of relatively extreme voters who interact online should be electorally meaningful, as politicians should perceive a benefit in moving to more radical positions. Second, there must be a larger share of extreme voters in places with higher Internet access and, therefore, displaying higher social media activity than in places with lower access. And third, the potential variation in extremeness among voters must precede the extreme views of politicians, as my rationale is that politicians are following voters. I denominate this hypothesis the extrinsic channel. It reads as follows:

H2a. Extrinsic channel: Political elites may acquire extreme views in response to an increasing share of voters who manifest themselves online, have increasingly acquired extreme positions, and represent a significant segment of the electorate.

The second reason why social media can affect elite extremeness relates to the internal dynamics of the digital world. Previous research has shown that extreme politicians in the United States achieve higher engagement and circulation on social media as compared to more mainstream ones (Hong and Kim, 2016). In other words, it is plausible that in Chile, social media users also reward extremeness, allowing politicians to reach a larger audience. Consequently, they may transpose this behavior to the offline domain, as they might be afraid of bad publicity arising from upsetting their online followers, even if there is no apparent electoral benefit in doing so. Put another way, politicians who are popular online may be "kidnapped" by this audience, even if such voters do not represent a significant portion of the electorate.

If this mechanism is true, then we should observe that negative messages have greater online circulation than positive ones, and that ideologically extreme politicians are the ones posting such negative messages. Consequently, the intrinsic channel hypothesis reads as follows:

H2b. Intrinsic channel: Politicians may acquire extreme views because extremeness are rewarded on social media, regardless of the positions of politicians' constituencies.

# 3G and Social Media in Chile

Mobile Internet services were launched in Chile in 2005, although it achieved little penetration until the first years of the 2010s. However, with the roll-out of 3G technology, access to mobile Internet expanded rapidly. As shown by table A1, the number of people covered by 3G greatly increased between 2010 and 2014. In 2014, 4G technology was introduced, resulting in practically universal coverage by 2019. Figure 1 shows 3G coverage in 2011 and 2015 per municipality in the most populated parts of the country - the metropolitan region - where the darker spots represent a higher share of 3G. The map suggests that there was an important spatial variation and an overall upward trend between both periods.[4]

The expansion of 3G was conducted through a concession system. In 2008, the Chilean Subsecretaria de Comunicaciones called for a public tender of the radioelectric spectrum, which allowed the three incumbent telecommunications companies to participate, and promoted the entry of more competitors.[5] The public tender ended in September 2009, resulting in a market of five competitors, as two new companies were able to operate in three available frequency blocks.[6] Nonetheless, the market was heavily concentrated in three companies - Claro, Entel, and Movistar - until 2016, when Wom acquired a higher market share.[7] Note that the 3G roll-out was not affected by short-term political interests since elected officials in parliament did not influence settlement patterns. On the contrary, it was a process directed by the central government and adjudicated upon based on transparent standards.

During these years, Chileans became heavy consumers of social media. Polling data show that the number of frequent consumers of social media for political news largely increased in the 2010-2020 period, as can be seen in Figure 2. Moreover, table 1 confirms that social media tend to attract more partisan users: indeed, both left and right-wing respondents are clearly over-represented on

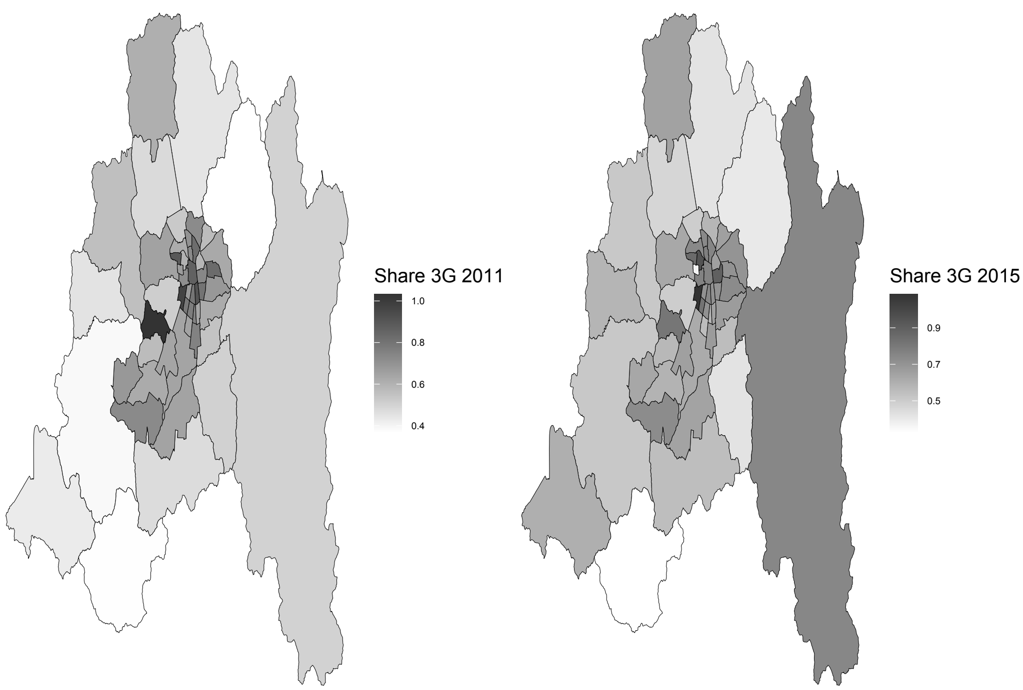
[4]Note that compared to other Latin American countries today, Chile has the highest internet usage, comparable only to Argentina. See https://www.internetworldstats.com/stats15.htm

[5]See https://www.reuters.com/article/internet-telecomunicaciones-chile-movile-idLTAN1745027420080717

[6]See https://www.subtel.gob.cl/gobierno-introduce-mas-competencia-en-telefonia-movil-3g/

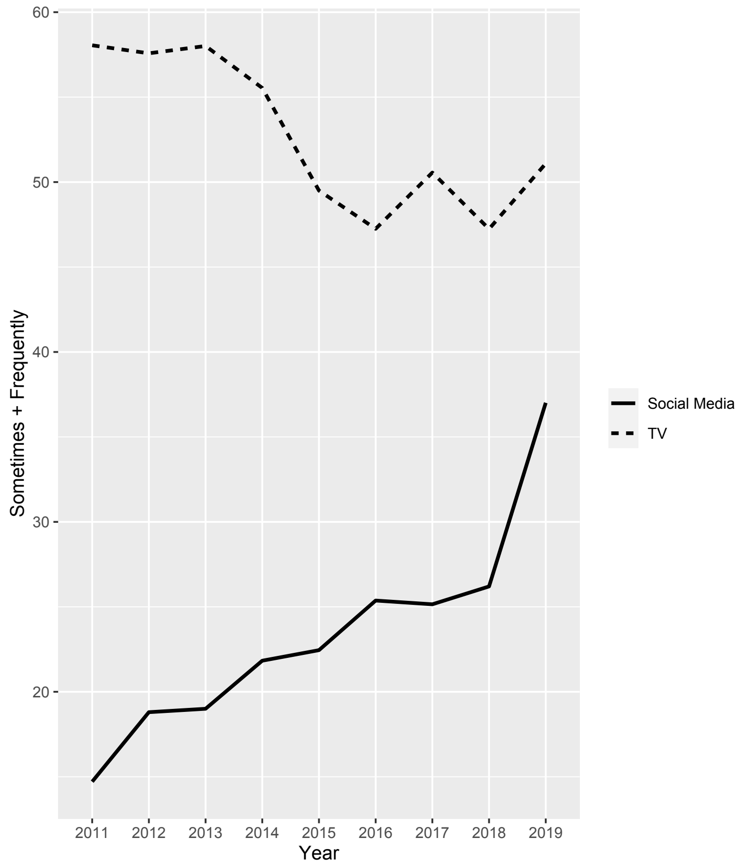
[7]See https://www.subtel.gob.cl/wp-content/uploads/2018/09/PPT_Series_JUNIO_2018_V1.pdf

Figure 1: Increase in 3G coverage Metropolitan Area Chile 2011-2015



social media[8], whereas a relatively small fraction of self-declared independents use these platforms.

Figure 2: Social Media and TV Consumption for Political News




Sources: Centro de Estudios Públicos

Table 1: Social Media Consumption by Ideology (Source: CEP 2019)

| Ideology | Social Media Consumer | Total Sample |
|---|---|---|
| Right | 20.5 | 10.7 |
| Center | 8.4 | 6.3 |
| Left | 32.7 | 15.2 |
| Independent | 38.3 | 67.8 |
| Total | 100 | 100 |

Certainly, Chilean politicians also started to use social media as a key source of political communication. table 2 shows the increase in Facebook pages[9] and in the yearly average number

[8]social media consumers are defined as respondents who declared that they follow political news on social media frequently.

[9]Facebook pages are used exclusively for political purposes. I did not include personal accounts.

of interactions, namely likes, shares and total reactions made in response to politicians' posts. By 2011, only 11% of politicians had a Facebook page, but this had increased to 90% in 2019. The average number of interactions also exhibits a similar trend.

Table 2: Average Number of Facebook Pages and Interactions by Year (Source: CrowdTangle)

| Year | Pages | Likes | Shares | Total interactions |
|---|---|---|---|---|
| 2011 | 0.11 | 0.3 | 0.01 | 0.3 |
| 2012 | 0.12 | 0.7 | 0.1 | 0.8 |
| 2013 | 0.21 | 3.9 | 0.5 | 5 |
| 2014 | 0.41 | 14.5 | 6.4 | 22.1 |
| 2015 | 0.53 | 26.4 | 18 | 47.4 |
| 2016 | 0.62 | 26.1 | 8.1 | 39.9 |
| 2017 | 0.70 | 55.9 | 11 | 85.8 |
| 2018 | 0.89 | 52.3 | 15.9 | 87.6 |
| 2019 | 0.90 | 67.5 | 46.1 | 152 |
| 2020 | 0.90 | 107.1 | 51.5 | 230.2 |

# Political Context

Besides considering the expansion of 3G internet and the penetration of social media in politics, it is also necessary to examine recent history and today's political context. From the return to democracy in 1989 until 2010, Chile was ruled by the center-left Concertacion coalition, an alliance that brought together the centrist Christian Democracy with a series of left-leaning parties, including the Socialist Party. The main opposition to this alliance came from a rightist coalition formed by the traditional center-right (National Renewal) and the Independent Democratic Union, a party that emerged from the Pinochet regime. This coalition won the presidency in 2010 and again in 2017.

In the 2010s, new parties - both on the left and the right - started to emerge, challenging the establishment of the post-authoritarian period. Indeed, a myriad of left-wing leaders gained national prominence after the student protests of 2011. Eventually, they formed their own parties, obtaining seats in congress in 2013 and becoming a relevant political force in 2017.

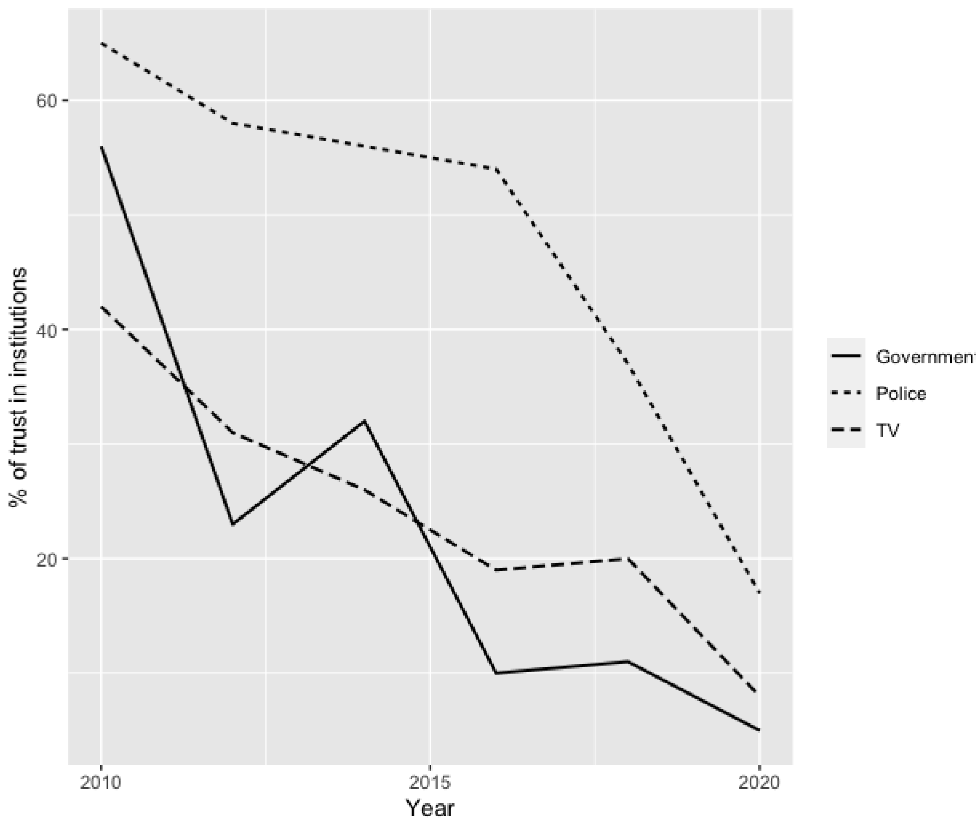
Before 2017, the electoral system to elect congress was an open-list PR system, where two seats were allocated in every district. To allocate seats, the system used the D'Hondt seat distribution formula. The presence of two representatives per district implied that, for a list to win both seats, it must have received twice as many votes as the second-best coalition (Argote and Navia, 2018). Thus, in most districts, the right and the center-left obtained one seat each. This electoral system was changed for the 2017 parliamentary election, when it became more proportional, with districts allocating different numbers of seats based on population (between three and eight). Unsurprisingly, after 2017, the Chilean congress incorporated more political parties, creating a very fragmented political landscape.

The incorporation of new parties on the fringes of the political spectrum and the reform of the electoral system have been deemed as factors explaining the rise in polarization. Indeed, scholars have seen increasing levels of polarization among voters that started around 2006 - first among voters and then followed by political elites - explained by a process of demobilization of centrist forces (Fábrega et al., 2018). In the last presidential election, the symptoms of polarization were pronounced, as the run-off for the presidential election was disputed between a far-left and a far-right candidate.

Increasingly, Chilean voters became skeptical OF and disaffected with traditional institutions, including the government, political parties, the church, the media, and the police. According to polling data from the think-tank Centro de Estudios Públicos, trust in the government declined from nearly 60% at the beginning of the 2010s to below 10% by 2020 (see table 3), and trust in the police and TV followed a similar pattern. Scholars have interpreted this phenomenon as a crisis of representation, meaning that political parties became unable to respond to social demands through the political process (Luna, 2016).

Nonetheless, social media do not follow the same pattern of increasing distrust in institutions. Figure 4 shows the percentages of Chileans who trust different types of media outlets. According to Cadem, a market research company, Facebook, Twitter, and WhatsApp are the only media outlets that increased their trust between 2018 and 2020, suggesting that the public believes in the

Figure 3: Trust in Institutions 2010-2020

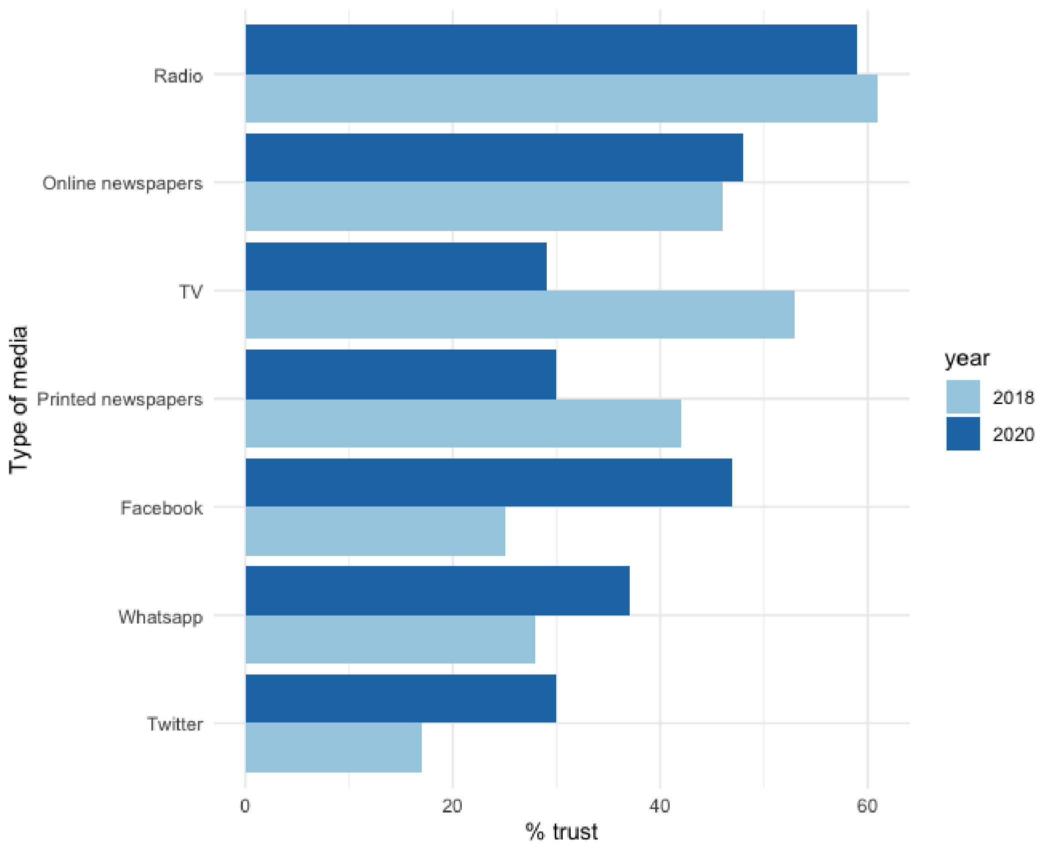



Sources: Centro de Estudios Públicos

information received from these channels, probably more so than from more established outlets.

This underlying distrust and skepticism toward democratic institutions went beyond the protests of October 2019, which accomplished nothing less than a change in the constitution that had governed the country since the return to democracy. It was the constitution created by the Pinochet dictatorship and further reformed by successive democratic governments.[10]

Figure 4: Trust in the Media 2018-2020




Sources: Cadem

[10]See Supplementary Material E for a description of this event and for an analysis of the role that social media played in it.

# Road map of the Empirical Analysis

The empirical analysis is divided into three parts. First, I examine the relationship between 3G mobile internet and the amount of attention politicians pay to social media. Second, I present the models relating 3G and Facebook activity with elite ideological extremeness, together with conducting some robustness checks. Finally, I explore the intrinsic and the extrinsic channels, which could plausibly explain the findings displayed previously. In Supplementary Material A, I discuss the challenges for causal identification and my proposed solutions.

# 3G and Attention to Social Media

## Data, Measures, and Empirical Strategy

To discover whether politicians engage more with social media as 3G mobile internet increases, I use several sources of data.[11] The independent variable - 3G access - was constructed using maps of global 3G network coverage from 2011 to 2018 provided by Collins Bartholomew's Mobile Coverage Explorer. This dataset includes 1*1 kilometers grid cells, showing the presence or absence of internet coverage at this geographical level. I combined this data with a proxy of population density obtained from the Socioeconomic Data and Applications Center, a data center owned by the NASA's earth observing center.[12] In order to create a continuous variable of the share of the population covered by 3G at a given level, I followed the same procedure as Guriev et al. (2021). In addition, I estimated the effect of the introduction of 4G in 2015 using the share of citizens covered by 4G.[13]

[11] See Supplementary Material B for a longer explanation of how I constructed the datasets used in this paper.

[12] This data is available at https://urs.earthdata.nasa.gov/

[13] The data of 4G from Collins Bartholomew did not vary over time, so it was probably less precise than the one from 3G. Thus, it was not possible to create a treatment variable at different periods. Hence, I defined the main predictor as the share of people covered by 4G in 2015. For this reason, in these models, I restricted the sample to the 2013-2017 congressional session because there was no variation in the other sessions.

To capture social media interactions between politicians and the public, I used Facebook measures of activity provided by the platform CrowdTangle. The first outcome is equal to one if a politician opened a Facebook page; otherwise it is zero. Moreover, I used the yearly average number of likes, shares, and total interactions; the latter includes other expressions, such as sad, angry, and laugh. Given the long tails of the distributions of this count variables, I used the formulas $log(1 + likes)$, $log(1 + shares)$ and $log(1 + total)$.[14] It is worth mentioning that a share is a more costly action than a like since it reveals a more significant commitment.

The dataset is constructed at the politician*year level, including all members of the Chamber of Deputies in the 2011-2018 period. In total, there are 258 unique politicians, considering that many were reelected either in 2013 or 2017.

To identify the effect of access to the internet on Facebook activity, I estimated a two-way fixed effect model, where the main predictor indicates the share of 3G coverage. As a robustness check, I estimated models with lead versions of the 3G variable, will indicate whether there was a pre-trend that might have challenged the validity of potential effects.

The econometric model can be described as follows:[15]

$$Y_{idrt} = \alpha + \beta(3G)_{drt} + \gamma_{idr} + \lambda_{rt} + \epsilon \quad (1)$$

Where $Y_{idry}$ represents the outcome of interests of politician $i$, in district $d$, in region $r$ in time $t$; the treatment of interest corresponds to $3G$, indicating the share of 3G coverage in district $d$. The parameter of interest is $\beta$, corresponding to the main effect. The parameter $\gamma$ represents politician*district fixed-effects, which is adjusted for any heterogeneity across politicians*districts which are constant over time. Moreover, $\lambda_{rt}$ constitutes year*region fixed-effects, which accounts for over-time variation in a given region. This is particularly relevant, given the regional differences in 3G access. Thus, the source of variation is within politicians in a given district over time; in other

[14] I assigned the value of zero to the period before the politician opened an account, as there were zero interactions on Facebook.

[15] For the sake of space, I did not include the equation using 4G as the treatment. It is equivalent to equations 1 and 2, but with a 4G variable instead of 3G.

words, the estimated effects correspond to a change of behavior in a politician who became more exposed to 3G at some point of their tenure in office compared to other politicians who did not. In addition, I present models controlling for district and individual-level covariates: political coalition, politicians' vote share, log of population, log of average income, the share of urban population, and the average age in the district.[16]

## Content Analysis

The models described in the previous section allow one to determine whether access to the internet at the district or municipality level affects the level of attention politicians pay to social media. However, we are still missing a key point: what are politicians saying on Facebook?

To explore this theme, I use topic modeling. This unsupervised machine learning technique allows one to characterize the main topics present in a set of documents by identifying words patterns within them. In a panel data structure, this analysis describes how certain topics become more relevant over time. In particular, topic modeling detects the $k$ number of topics for a given document. For each $k$ topic, there is a distribution of words. In this sense, document $i$ can be characterized by a distribution of topics $k$ and, in turn, topic $k$ includes a set of words in different proportions. The share of each document for each topic is also denominated the "mean contribution." I use a Latent Dirichet Allocation (LDA) topic modeling, which utilizes a prior distribution called Dirichet for the per-document topics and the per-topic words. In my case, the unit of analysis - or documents - are Facebook messages per year, separated by politicians in districts with high and low access to 3G, in order to compare the potential differences by level of internet access.[17] Thus, the topic modeling results differentiated by 3G access (high or low) are presented.

The main advantage of this approach is that the researcher does not decide ex ante what topics emerge (Catalinac, 2016). Rather, the researcher must choose the number of topics to

[16] As an additional test, I exploit variation of 3G across municipalities within districts. See Supplementary Material C for this analysis.

[17] I define High 3G as being above the median.

estimate the model and interpret the substantive meaning of each topic by analyzing the most common words. Generally, scholars pick a given number of topics, run the specification, and then change the number of topics based on substantive meaning (Grimmer, 2010). The intuition is that more topics allow one to "zoom in" on narrower themes (Catalinac, 2016), whereas a lower number creates more comprehensive topics. Following this approach, I started by selecting twenty topics,[18] and I analyzed their substantive meaning by looking at the most common words. Then, in the subsequent analysis, I reduced the number of topics because it was difficult to distinguish some topics from others. Every time, the results were fundamentally the same, with some slight variations.[19]. In the analysis, I present the model results with eight topics. [20]

It is worth noting that in the early 2010s, just a few legislators had a Facebook page, so the topics that emerged could outweigh the handful of legislators on Facebook. However, as shown in table 2, there has been a steady increase in Facebook pages over time, implying that the topics became more representative of all legislators after 2014.

## 3G Increases Attention

Clearly, internet access has a big effect on Facebook usage among Chilean politicians. table 3 shows the impact of 3G access on different measures of Facebook activity. As all models adjust for politician*district fixed effects and for regional time trends, these results mean that changes in 3G coverage within districts substantively increase Facebook interactions over time for the average politician. The most critical result refers to the opening of a Facebook page - displayed in columns 1 and 2 - since it is a clear behavioral outcome, whose interpretation is straightforward: an additional unit increase in 3G access augments the chance that a politician opens a Facebook profile page by 45 percentage points, a very substantial effect.[21] Likewise, column 4 shows that the marginal effect

[18] I selected a relatively low number of topics because there is not much variation in the type of Facebook messages sent by politicians, so it did not make sense to zoom in too much on specific themes.

[19] See Supplementary Material D for a description of the results with varying values of $k$

[20] For the analysis, I removed Spanish stopwords, such as "de," "y," and "es," and words that were repeated in many posts, for example, "Ahora," "Chile," and "Hoy."

[21] The variable share 3G is coded between 0 and 1. Consequently, a one-unit increase means going from zero 3G to a 100%. Another way to interpret this coefficient would be to divide it by 10. In that case, it

Table 3: Effects of 3G Coverage on Facebook Activity

| | (1) Pages | (2) Pages | (3) Likes | (4) Likes | (5) Total | (6) Total | (7) Shares | (8) Shares |
|---|---|---|---|---|---|---|---|---|
| Share 3G | 0.462* | 0.453** | 1.570*** | 1.414** | 1.674*** | 1.505** | 0.585 | 0.436 |
| | (0.232) | (0.219) | (0.536) | (0.594) | (0.585) | (0.662) | (0.390) | (0.404) |
| Adjusted | No | Yes | No | Yes | No | Yes | No | Yes |
| $R^2$ | 0.755 | 0.760 | 0.781 | 0.784 | 0.782 | 0.785 | 0.781 | 0.786 |
| Obs. | 826 | 814 | 826 | 814 | 826 | 814 | 826 | 814 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. Adjusted models control for log of population, log of income, urban status, average age, vote share, and political coalition. See table SF1 in Supplementary Material F for a complete table including the control variables.

of 3G access increases enormously the number of likes, which is not surprising considering the effect described before. In this sense, the evidence confirms that access to the Internet increases the attention politicians pay to social media.

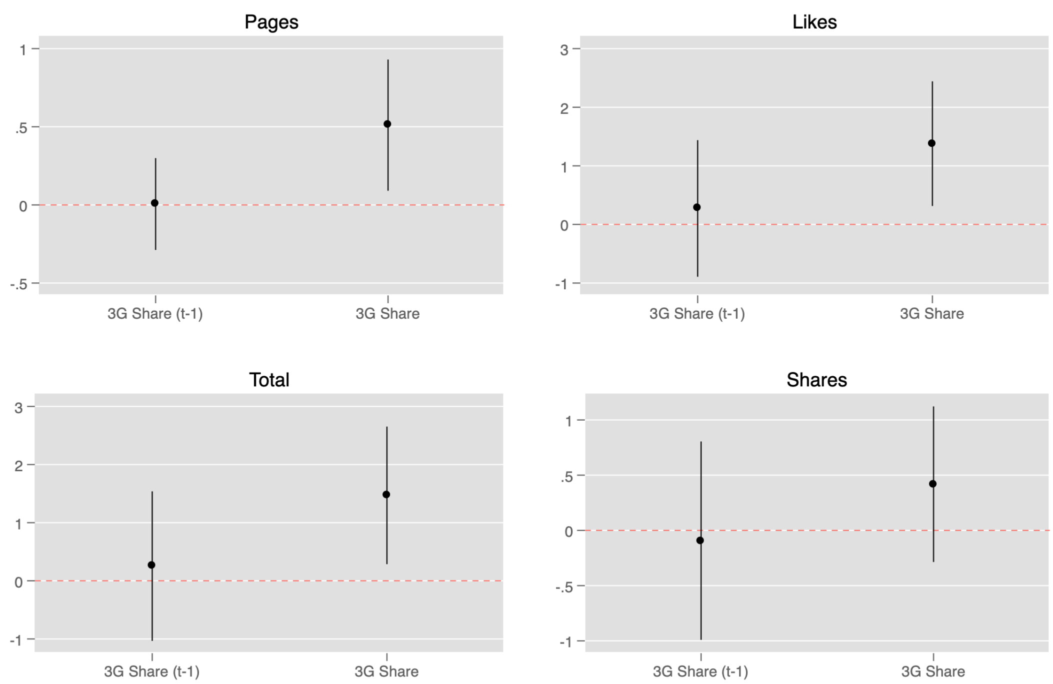
Figure 5 shows a visualization of the previous results, including the lead versions of 3G. The figure confirms that the impact of 3G is not explained by a previous trend on districts that gained access to 3G. On the contrary, the effect appears after the installation of 3G, which supports the robustness of these findings.[22] table A3 shows the model with a two-lagged version of the 3G variable. We see that the effect of 3G on opening a Facebook page is immediate, where the impact on interactions - likes, total interactions, and shares - appears the year after or even two years after. This makes sense since politicians need to build a group of followers before getting reactions to their messages.

Regarding the impact of 4G, we do not see a significant effect. Indeed, the introduction of 4G did not impact any of the measures of Facebook activity (see table A4), probably because those

would read as "a 10 percentage-point increase in 3G increases the probability of opening a Facebook page in 4.5 percentage-points."

[22]See table A2 for a model with two 3G leads. I was not able to include more than two leads because the sample size was greatly reduced. As my dataset begins in 2011, for many districts, I do not have more than two periods before the increases in 3G. Also, I was not able to include leads and lags in the same model due to lack of observations.

Figure 5: Coefficient Plot Effects of 3G on Facebook Activity




The circle represents the point estimate, and the line the 95% confidence interval. See table SF2 in Supplementary Material F for a corresponding table including the control variables.

districts that received 4G already had high access to 3G.

The next step of this analysis is to explore the content of messages of politicians' Facebook posts through topic modeling. The algorithm distinguishes two main prevalent topics for legislators in high 3G districts. I call the first topic "Personal appeal," as its main words are as follows: "contact me," "help," "sincerely" and "support." In this sense, the topic relates to a direct appeal to voters, encouraging them to contact legislators to voice their concerns, highlighting that they will support them. The second is focused on the legislative process itself, highlighting what the legislators are doing on a daily basis in parliament. This is characterized by the words "bill," "project," "development," and "reform." The translated keywords for each topic is displayed in table 4.

Table 4: Main Words Topics High 3G Access

| **Policy** | **Appeal** |
|---|---|
| Project | Best |
| Government | Effort |
| Municipality | help |
| Jobs | Contact me |
| Law | Support |
| Region | Always |
| Education | Make |
| Health Care | Government |
| National | Online |
| President | Law |
| Chamber | Sincerely |

Importantly, the mean contribution of each topic radically changed over time. Panel a) in Figure A2 shows that the topic "Personal appeal" substantively decreased its mean contribution after 2012, which coincides with the period when more politicians opened Facebook pages. In turn, communication about the legislative process became by far the most prevalent topic by 2018. Thus, politicians increasingly use Facebook to communicate about bills, votes, and projects but not to gather information about voters' demands. Note that the number of Facebook pages is not fixed over time, so this change probably reflects that more legislators opened a Facebook page during the decade, as shown in table 2. Still, it confirms that legislators mostly use Facebook to confirm their own actions in the legislative process.

Regarding legislators in low 3G districts, the topic modeling algorithm finds just one relevant topic - Legislative process.[23] In other words, among low 3G districts, the "Personal appeal" topic is not observed. Panel b) in Figure A2 plots the mean contribution of the "Legislative process" topic by 3G status, showing that nowadays, in both type of districts, most politicians use Facebook to send messages about legislative issues.

The topic model analysis suggests that politicians use Facebook as a unidirectional form of communication, as they are not concerned about responding to specific demands. This suggests that they might be worried less about the reactions to their messages than gathering local information for their legislative endeavor.

# Extremeness

## Data, Measures, and Empirical Strategy

The second part of the empirical analysis relates 3G coverage and social media usage to elite extremeness.[24] I define ideological extremeness as the absolute deviation on the left-right scale of legislator $i$, with respect to the average legislator of year $y$.

It is worth discussing whether the left-right scale is adequate to measure extremeness in the Chilean context. Within Latin America, Chile has one of the most stable party systems. There are historical parties that represent clear ideological stances, such as the Socialists and the Communists on the left and the Republican Party and Independent Democratic Union on the right. Previous research has shown that such parties clearly align with their declared ideologies in their legislative behavior (Argote and Navia, 2018). Thus, this is the most meaningful construct that separates parties, and deviations from this scale are the most adequate way to measure extremism.

To measure this construct, I used the roll-call voting data of the Chilean Chamber of Deputies,

[23] See Supplementary Material D for a descriptive explanation of the topics found among the low 3G group.

[24] Another plausible behavioral outcome would have been the disbursement of resources, as Bessone et al. (2019) did. However, Chilean legislators do not have the power to allocate fiscal resources to their localities.

which includes all votes from the 2011-2020 period. Then, I created an original measure of extremeness following this procedure: First, I computed the DW-nominate scores, which created a measure of politicians' ideal points on the left-right scale based on roll-call voting data in congress. The algorithm uses the whole set of bills for the legislative sessions between 2011-2020, which includes 7953 votes, covering a myriad of areas. table A7 show the share of topics discussed in the 2011-2020 period.[25] Second, based on the DW-nominate scores on the left-right dimension, I created a measure consisting of deviations from the average ideological positioning in a given year, which can be described as follows:

$$Extreme = |(wnom_{iy} - wn\bar{o}m_y|$$

Which indicates the deviation of politician $i$ in year $y$ from the average ideological position of the congressional session of year $y$. The higher values of this measure indicate larger deviations from the average legislator, and therefore, higher extremism. The maximum value is approximately 1.2 while the minimum is around zero. Note that this measure was used by Hong and Kim (2016) to study the correlation between extremeness and Twitter audiences in the US.

I want to discuss the merits of this variable. DW nominate scores are typically used as a measure of latent ideology in American politics. Indeed, scholars have used it to show the increasing levels of polarization between Democrats and Republicans (e.g. Ladewig, 2021) and for analyzing the impact of close elections on ideological positioning (e.g. Lee et al., 2004). I use this variable mainly because it incorporates the whole set of non-unanimous roll-call votes without cherry-picking any particular vote that we may think reveals extremeness. The other option would have been exactly that: pick a few votes of important bills per year, decide ex ante which option indicates an extreme position, and use it as the outcome. I decided against this option precisely because there are several arbitrary decisions involved. For instance, there might be votes that we can consider extreme, such

[25] The DW nominate packager omits all unanimous bills, defining unanimous as when more than 97.5% of congress agree on a bill.

as the attempt to impeach the president in 2019. However, the impeachment was practically split along party lines, as the opposition took it as a display of strength. So the definition of being "extreme" would apply to all deputies of one side of the political spectrum. Therefore, by using latent ideology in all roll-call votes, I relied on a measure that includes most of the bills per year, avoiding such arbitrary decisions - choosing bills and defining what is extreme.

Another option would have been to use the absolute deviation with respect to the average ideological position in the whole period, and not by year. I also decided against this option because, in measuring extremeness, it is important to adjust for the composition of congress in a particular year. For instance, if congress is especially leftist, for a stance to be considered extremism, a left-wing legislator would have to move to even more radical positions. In the case of a right-wing one who has not changed position, it would also be considered more extremist than before in this new left-wing congress, which makes sense because now the median legislator is more to the left. Thus, a measure of extremeness that adjusts for the position of the average legislator in a yearly basis captures more adequately the level of extremeness. That being said, the over-time average of this measure is very stable - always in the range 0.65-0.78 (see table A5), meaning that there are no dramatic changes in the median legislator.

In general, the extremeness measure has a normal distribution. Figure A3 displays histograms of this variable on a yearly basis, showing that the distribution approaches normality, although there are some years where there is a higher skewness (2012 and 2020). As this variable is measured in absolute deviations from the average, it implies that most legislators moderately deviate from the yearly average, as they represent different political parties. However, just a few legislators could be classified as extremist since it is unusual to exceed the threshold of one.

A glance at the most extreme legislator each year confirms the validity of this measure as a proxy of ideological extremism. table A6 shows that from 2011 to 2013, the most extreme legislators were from the Communist Party, which is not surprising given their history and their current positions, their support for the Maduro regime in Venezuela, and the embracing of the Soviet Union in the past. However, between 2014 and 2017, the most extreme legislators belonged to the right, typically to the Independent Democratic Union, the party that emerged from the Pinochet dictatorship. In the 2018-2020 period, the extremist legislators were, again, from left-wing parties which formed a coalition with the communists. It is worth noting that the most extreme politicians always belong to the opposition -when the right governs, they are from the left and vice versa. This is likely because being in government creates incentives for aligning with the executive.

The econometric model relating access to the internet and ideological extremism can be described as follows:

$$Extreme_{imrt} = \alpha + \tau(3G)_{drt} + \gamma_{idr} + \lambda_{rt} + \epsilon \tag{2}$$

Where the outcome $Extreme_{imrt}$ is regressed on 3G access, including politician*year and year*region fixed effects.

The parameters estimated in equation four are meaningful because, as demonstrated in the previous results section, access to the internet increases politicians' attention to social media. If paying attention to social media affects extremeness, then 3G should be a proxy for social media activity. However, we can estimate a model that tests this proposition more directly by including interactions in Facebook as *independent variables*. With such a model, there is a risk of reverse causality, since both measures - interactions in Facebook and extremeness - are yearly averages and, therefore, are computed almost simultaneously. Therefore, I used a lagged version of the independent variables; that is, I regressed extremeness on year $t + 1$ on Facebook interactions in year $t$.[26] The model can be described as follows:

$$Extreme_{idrt+1} = \alpha + \mu(FB)_{drt} + \gamma_{idr} + \lambda_{rt} + \epsilon \tag{3}$$

Where the variable $FB$ accounts for Facebook interactions. In equation five, the parameter

[26] In this model, I was able to use more years (until 2020), because I was not including the 3G variable, which covered until 2018. Thus, I was able to include more leads and lags than in the results of the previous section, as displayed in Figure 6.

of interest is $\mu$, the effect of Facebook interactions in the previous year. An alternative specification would have been to control for access to 3G. Such a strategy is not convincing since I am interested in how social media activity, which 3G enhances, affects elite extremeness. Thus, it is better to avoid conditioning on access, as the quantity of interest is precisely the variation between politicians with high and low access.

Note that the models described in equations two and three adjust for politician-district fixed effects and region-specific time trends, implying that the source of the variation is within politician. In this sense, we can rule out that results can be explained by the selection of extreme politicians in recent years or because of radical changes in ideological positions among parties.

As an extra robustness check, I estimated an additional specification. Specifically, I instrumented Facebook pages, likes, and total interactions with access to 3G at the district level, conditional on district-level covariates (population, income, urban status, average age), individual controls (vote share and political coalition), and politician-district and region-year fixed effects.

It is worth discussing the main assumptions of instrumental variable specification. The exclusion restriction requires that, conditional on the fixed effects and in the control variables, the only path in which access to 3G internet affects elite extremeness is through its impact on Facebook activity. In other words, the identifying assumption is that changes in 3G within districts affect variation in extremeness due to increasing levels of activity on Facebook among elites.[27] This assumption is voided if, for example, there are increases in 3G access changes perceptions among voters, which in turn can lead politicians to alter their behavior. Moreover, 3G allocation across districts is not random, as, for example, urban areas have more connectivity than rural ones. To overcome these issues, I explicitly addressed the possibility that voters might explain this result (see Extrinsic Channel section) and I adjusted for several district-level covariates (described in the table notes of the main results) to increase the validity of the results.

[27] The valid first stage assumption means that access to 3G affects Facebook consumption. This is proven in table 3.

The first stage of this model is as follows:

$$Page_{idry} = \alpha + \mu(3G)_{dry} + \gamma_{idr} + \lambda_{ry} + \epsilon \tag{4}$$

Where $Page_{idry}$ of legislator $i$, in district $d$, in region $r$, in year $y$ is instrumented by the share of the population in the district covered by 3G, adjusting for politician*district fixed effects and regional time trends. For the other measures - likes and total interactions - I ran the same specification but changed the outcome variable in the first stage. The second stage can be described as follows:

$$Extreme_{imry} = \alpha + \hat{Page}_{idry} + \gamma_{idr} + \lambda_{ry} + \epsilon \tag{5}$$

Where the variable of legislative extremeness is regressed on the predicted value $\hat{Page}$, adjusted by politician-district and country-region fixed effects.

## Facebook Increases Extremism

table 5 shows the impact of 3G coverage on extremeness in congress. In columns 1 and 2, we see a positive effect of 3G on extremeness, although it is not statistically significant at conventional levels; when adding a lagged term, we see a similar result.

table 6 shows the effects of Facebook activity on extremeness. Again, to avoid reverse causality, I estimated the models using all independent variables for the year before the outcome. Clearly, there is a positive effect of Facebook activity on extremeness. For instance, column 2 shows that opening a Facebook page in year $(y-1)$ increases a politician's extremeness levels in 0.045 units; similarly, column 8 shows that the marginal effect of a 1% growth in shares causes a 0.032 increment in extremeness. These findings suggest that internet access by itself does not seem to impact elite behavior. However, when considering Facebook interactions in the previous year as a treatment, a strong impact can be seen.

Table 5: Effects of 3G on Extremeness

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Share 3G | 0.098 | 0.070 | 0.109 | 0.085 |
| | (0.076) | (0.066) | (0.077) | (0.064) |
| Share 3G lagged | | | 0.030 | 0.030 |
| | | | (0.056) | (0.056) |
| Adjusted | No | Yes | Yes | Yes |
| $R^2$ | 0.726 | 0.774 | 0.799 | 0.799 |
| Obs. | 826 | 814 | 656 | 656 |

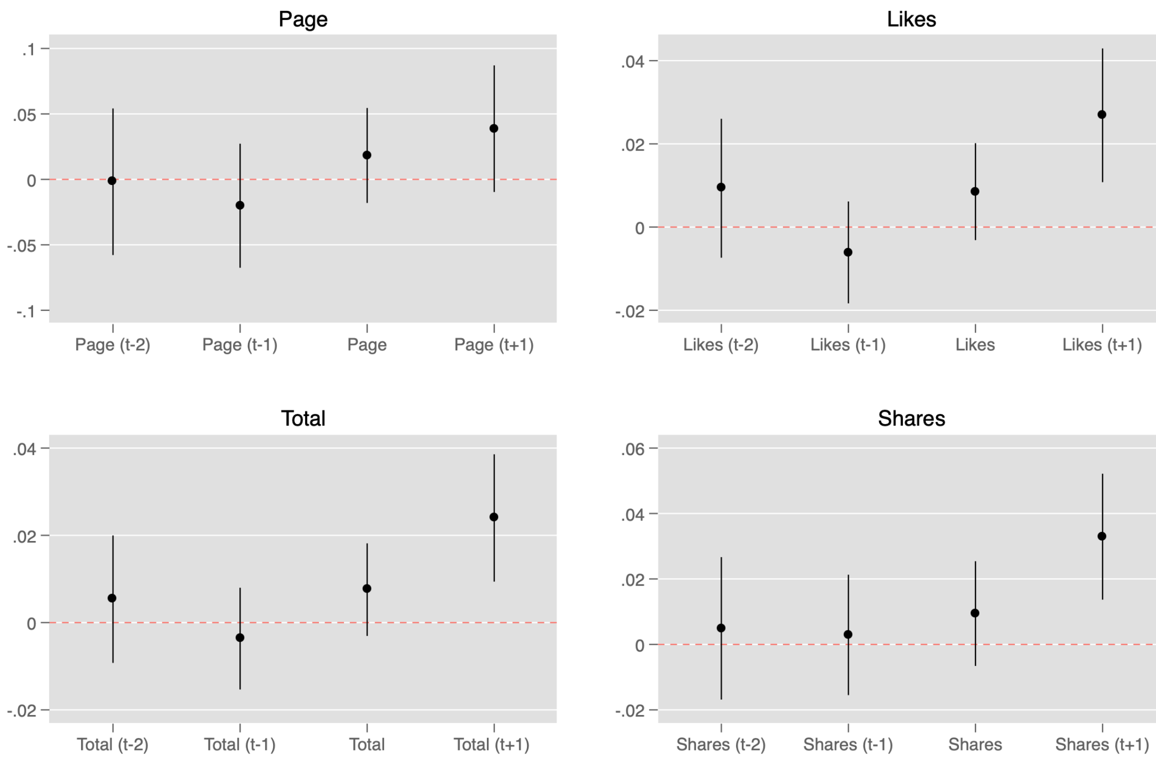
*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. The outcome for all regressions is the level of extremeness in congress. All models include politician*district and region*year fixed effects. Adjusted models control for 3G coverage, vote share, log of population, log of income, urban status, average age, and political coalition. See table SF6 in Supplementary Material F for a complete table including the control variables.

Table 6: Effects of Facebook Activity on Extremeness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Page | 0.043 | 0.045* | | | | | | |
| | (0.026) | (0.024) | | | | | | |
| Likes | | | 0.029*** | 0.026*** | | | | |
| | | | (0.009) | (0.008) | | | | |
| Total | | | | | 0.027*** | 0.024*** | | |
| | | | | | (0.008) | (0.007) | | |
| Shares | | | | | | | 0.039*** | 0.032*** |
| | | | | | | | (0.009) | (0.008) |
| Adjusted | No | Yes | No | Yes | No | Yes | No | Yes |
| Obs. | 1145 | 1137 | 1145 | 1137 | 1145 | 1137 | 1145 | 1137 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2020. The outcome for all regressions is level of extremeness in congress. The models include politician*district and region*year fixed effects. The adjusted models control for log of population, log of income, urban status, average age, vote share, and political coalition. See table SF7 in Supplementary Material F for a complete table including the control variables.

Figure 6: Coefficient Plot Effects Facebook Activity on Extremeness




The circle represents the point estimate, and the line the 95% confidence interval. See table SF8 in Supplementary Material F for a corresponding table including the control variables.

The coefficient plot displayed in Figure 6 confirms the findings presented above. The effect of Facebook activity on extremeness becomes significant a year after the exposure, and not in the year before. Therefore, we can discard the notion that the results are explained by a previous trend. Moreover, it seems that the effects are greater regarding the amount of likes compared to having a page, suggesting that the reactions to politicians' posts are the most relevant factor.

The results of the instrumental variable specifications (table 7) are also consistent with the previous findings. We see a positive effect of Facebook activity on elite extremeness, especially with regard to likes, total interactions, and shares; on the other hand, we do not observe a significant effect for having a Facebook page. In this sense, I confirm that the level of Facebook activity seems to impact extremeness, especially the act of sharing a politician's post.

Table 7: Instrumental Variable Estimates. Outcome: Extremeness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Page (t+1) | 0.118 | 0.077 | | | | | | |
| | (0.111) | (0.102) | | | | | | |
| Likes (t+1) | | | 0.109*** | 0.076** | | | | |
| | | | (0.040) | (0.033) | | | | |
| Total (t+1) | | | | | 0.139*** | 0.068** | | |
| | | | | | (0.041) | (0.030) | | |
| Shares (t+1) | | | | | | | 0.254*** | 0.137*** |
| | | | | | | | (0.071) | (0.048) |
| Adjusted | No | Yes | No | Yes | No | Yes | No | Yes |
| Obs. | 773 | 773 | 780 | 773 | 773 | 773 | 773 | 773 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. The adjusted models control for log of population, log of income, urban status, average age, vote share, and political coalition. See table SF9 in Supplementary Material F for a complete table including the control variables.

Taken together, the results presented in this section suggest a positive effect of social media activity on ideological extremeness. In the next section, I explore the plausible channels explaining this effect.

# Mechanisms

Before describing the exploration of mechanisms, I want to warn the reader that testing for mechanisms is not an easy task. For instance, the fact that negative posts written by politicians may gain higher circulation does not necessarily imply a connection between elite extremeness and Facebook activity; the same applies to a potential connection between voters' radicalism and elite radicalism. However, if we do find evidence for these channels, then it is more plausible that these are connected to elite extremeness than in the opposite case. Thus, even if these empirical analyses are not definite proofs, they could give us some clues about the reasons behind the empirical results already presented.

## Extrinsic Channel

In this section, I explore the possibility of the extrinsic channel: that is, voters who might be increasingly skeptical of democratic institutions would be the driving force behind elite extremeness. Thus, I examine a plausible increase in voter radicalism among districts with higher access to 3G, which could be related to increases in elite extremeness.

For this purpose, I use individual-level polling data from the Lapop survey, a nationally representative public opinion poll of several Latin American countries. In this case, I use the observations of Chile for the 2012, 2014, 2017, and 2019 waves.[28] I merged this data with the 3G share variable at the municipal level over time, resulting in a repeated cross-sectional dataset, covering 119 of the 345 Chilean municipalities.[29]

As the main dependent variables, I use two measures of skepticism towards democratic institutions, which are, arguably, proxies of anti-democratic attitudes. The first variable is the extent

[28] As with any public opinion poll, the Lapop survey is not representative at the municipality level, so there could be a threat to the external validity of this analysis. However, as I use multiple waves, there is a decent number of observations per municipality - 110 individuals on average. Still, I caution that the sample most likely over-represents urban places, as many rural locations are not typically reached by these types of polls.

[29] Given that the 3G data covers until 2018, I merged the 2018 3G data with the 2019 Lapop survey.

to which the respondent agrees with the following statement: "Despite its problems, democracy is better than any other form of government." This variable is routinely used in the Lapop survey and other public opinion polls to measure attitudes towards authoritarianism, as distrust in democracy implies an openness towards other regimes. In this survey, the original variable used a seven-point scale, where one meant "Strongly Disagree" and seven "Strongly Agree." From this measure, I created an indicator variable equal to one if respondents answered either six or seven - that is, if they agreed with the statement - and zero otherwise.

The second variable was constructed from the following question: "To what extent do you trust in Chilean elections?" Again, this measure touches upon the most basic act in a democracy, namely voting, to choose the main authorities. This variable also used a seven-point scale, where seven means "A lot of trust." Similarly to the support democracy measure, I created a dummy variable equal to one if respondents answered either six or seven - that is, if they trust in elections.[30]

I first provide descriptive evidence of trends in these variables, separated by high and low 3G access (above or below the median), to see if, in districts with high 3G, there were higher levels of voter radicalism that may have eventually led politicians in high covered areas to acquire extreme positions.

Then, I estimate an econometric model, using municipality and year fixed effects, to analyze whether changes in 3G at the municipality level correlate with changes in voters' radicalism. The regression equation can be written as follows:

$$Y_{imy} = \alpha + \omega(3G)_{my} + \gamma_m + \theta_y + \epsilon \tag{6}$$

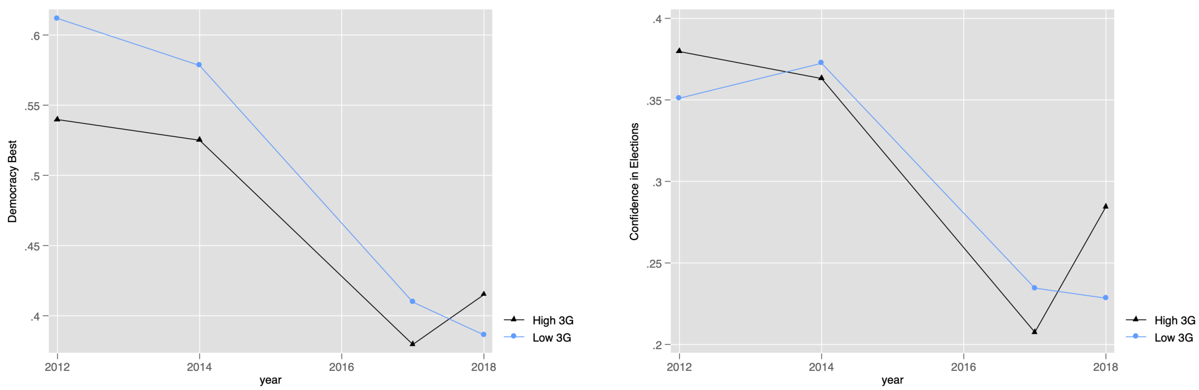
Where the dependent variable for respondent $i$ in municipality $m$ in year $y$ is regressed on 3G access at the municipal level. The coefficients $\gamma$ and $\theta$ account for municipality and year fixed effects, respectively. The parameter of interest is $\omega$, the impact of an additional percentage-point of access to 3G on the probability of supporting democracy, or in the chance of trusting elections.

[30] As a robustness check, I used the original scales for both of these outcomes. The results are in table **??**.

Crucially, I estimate this model before and after at least one legislator covering such a municipality created a Facebook page. If we observe an effect before any politician creates a Facebook account, then they might influence subsequent elite behavior; if not, we can discard the possibility that politicians move to extreme positions in response to voters.

### Results 3G and Public Opinion

Figure 7: Descriptive Trends Public Opinion




(a) Democracy Best Regime

(b) Confidence in Elections

Do voters drive the connection between Facebook activity and elite extremeness? The evidence suggests a negative answer. Figure 7 shows that in municipalities with both high and low levels of 3G access, there is an important decline in both trust in democracy and confidence in elections. Moreover, in the last wave of the survey (2018), there is an increase among the places with high 3G, which does not happen among the low 3G. In this sense, it is unlikely that politicians in covered areas have been following voters with regard to extremeness since there is not a distinct shift in extremeness in these areas.

The results from table 8 corroborate the previous insight. Indeed, before any legislator opened a Facebook page, there was no correlation between 3G access and support for democracy; in reality, a negative and significant effect relating 3G with support for democracy emerged only after politicians opened a Facebook page. In this sense, it looks like politicians who move to the

Table 8: Effects of 3G on Democracy Best Government (Before Facebook Page).

| | (1) Support Dem. | (2) Support Dem. | (3) Conf. Elections | (4) Conf. Elections |
|---|---|---|---|---|
| Share 3G | -0.278 | -0.284 | -0.324 | -0.163 |
| | (0.238) | (0.295) | (0.243) | (0.242) |
| Adjusted | No | Yes | No | Yes |
| $R^2$ | 0.189 | 0.217 | 0.148 | 0.177 |
| Obs. | 1737 | 1450 | 1840 | 1504 |

Effects of 3G on Democracy Best Government (After Facebook Page).

| | (1) Support Dem. | (2) Support Dem. | (3) Conf. Elections | (4) Conf. Elections |
|---|---|---|---|---|
| Share 3G | -0.310* | -0.349** | -0.161 | -0.133 |
| | (0.168) | (0.165) | (0.115) | (0.116) |
| Adjusted | No | Yes | No | Yes |
| $R^2$ | 0.0766 | 0.110 | 0.0562 | 0.0775 |
| Obs. | 3779 | 3188 | 3870 | 3258 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the municipality level. All models include municipality and year fixed effects. Adjusted models control for income, education, urban status, and gender. See table SF10 in Supplementary Material F for a complete table including the control variables.

extreme were not following public opinion. In addition, we can discard the notion that the exclusion restriction of the IV model, violated due to an increase in voter extremism due to 3G, could have affected politicians.

## Intrinsic Channel

In this section, I explore the intrinsic mechanism by analyzing whether negativity is rewarded on social media and whether extreme politicians are more likely to post negative messages.

To this end, I analyze the sentiments of Facebook messages over time, using the Spanish version of the R package "syuzhet," which contains the NRC Valence, Arousal, and the Dominance (NRC VAD) lexicon developed by Mohammad, Saif M. (2020). This dictionary is suitable for analyzing words or sentences, assigning a valence score to each of them based on seven emotions: anger, disgust, fear, joy, sadness, trust, and surprise. Each sentence receives a score for negative and positive sentiment, which is also called valence. The maximum value for each sentiment or emotion is seven, while the minimum is zero. For my analysis, I focus on two emotions, disgust and happiness, and two sentiments, positive and negative, since my theoretical interest is to analyze whether clearly negative emotions receive higher reactions on Facebook.

The NRC VAD dictionary was especially designed to analyze the sentiments and emotions of short sentences, such as Facebook messages or tweets (Kiritchenko et al., 2014). Moreover, it has been used in several research articles, covering issues from hashtags analysis (Mohammad and Kiritchenko, 2015) to movie dialogues (Hipson and Mohammad, 2021). To provide an example from my dataset, this is a Spanish sentence associated with a negative sentiment:

> "Se han perdido 30 mil puestos de empleo en lecherías y esta decisión de la comision antidistorsiones es una verdadera falta de respeto a nuestros productores lecheros"

In English, this sentence reveals a legislator complaining about the loss of employment in the milk-producing sector. Meanwhile, this is a sentence associated with joy:

"Un gran saludo y abrazo para tod@s que las energías del universo reinen en sus hogares y llege el amor, la paz y las esperanzas de un buen año nuevo 2020 de grandes desafíos para el pais, la región y en especial para nuestro querido puerto de Coquimbo, Bendiciones para ustedes y sus familias."

This is basically a message about love and peace in the context of the new year.

In my analysis, I correlate the average number of total reactions of politician $i$, likes and shares on the average sentiment (emotion) score, estimating a regression of the following form:

$$Log(1 + total)_{iy} = \alpha + \beta_1 (negative)_{iy} \tag{7}$$

$$Log(1 + total)_{iy} = \alpha + \beta_2 (positive)_{iy} \tag{8}$$

The idea is to compare $\beta_1$ and $\beta_2$; if the former coefficient is significantly larger than the latter, it means that negative posts have more circulation on Facebook than positive ones. Note that I don't include either politician or year fixed effects because my purpose is to see whether posts with higher reactions receive more negative sentiments across politicians; in other words, my interest here is not to correlate sentiment and reactions within politicians over time.

Moreover, I analyze the correlation between ideological extremeness and the negative sentiment of Facebook posts, estimating the following regressions:

$$Extreme_{iy} = \alpha + \beta_3 (negative)_{iy} \tag{9}$$

$$Extreme_{iy} = \alpha + \beta_4 (positive)_{iy} \tag{10}$$

If negative posts correlate with higher extremeness and positive posts do not, I expect $\beta_3 > 0$

and $\beta_4 = 0$.

### Results of Facebook Sentiments

The results from the sentiment analysis confirm that negative and angry posts are rewarded on social media. The top panel of table 9[31] shows a clear positive correlation between reactions - total, likes, and shares - negative sentiment, and, in particular, the disgust emotion. Indeed, column 1 shows that an additional unit of negativity increases total reactions by 38%. In the bottom panel, even if there is also a positive correlation, the magnitude is considerably lower, both in positive sentiment and in the happiness emotion.

table 10 confirms the positive correlation between extremeness and negative sentiments, and extremeness and the disgust emotion. On the other hand, there is no correlation between either positive sentiment or happiness emotion with ideological extremeness.

Taken together, the descriptive results presented in tables 9 and 10 suggest that a) there is a premium associated with being negative and exhibiting disgust, as these posts achieve higher engagement and b) extreme politicians are more likely to posts negative messages.

## Discussion

Throughout the history of representative democracy, strong and independent media have been considered a critical factor in holding the powerful accountable. However, in the last few years, the impact of social media on politics has been interpreted through a more pessimistic perspective, based on recent political events and the findings of the academic literature. Despite the growing evidence of the impact of social media on voters, a key question remains, namely do these effects on voters transpose onto politicians?

[31] The sample size is lower than in table 7 because in the early years, some politicians just posted videos or links, so it was not possible to conduct a sentiment analysis.

Table 9: Correlation Between Facebook Activity and Negative Sentiments.

| | (1) Total | (2) Total | (3) Likes | (4) Likes | (5) Shares | (6) Shares |
|---|---|---|---|---|---|---|
| Negative | 0.386*** | | 0.294*** | | 0.408*** | |
| | (0.068) | | (0.061) | | (0.062) | |
| Disgust | | 0.804*** | | 0.631*** | | 0.758*** |
| | | (0.191) | | (0.170) | | (0.176) |
| $R^2$ | 0.0446 | 0.0249 | 0.0327 | 0.0194 | 0.0586 | 0.0259 |
| Obs. | 697 | 697 | 697 | 697 | 697 | 697 |

Correlation Between Facebook Activity and Positive Sentiments.

| | (1) Total | (2) Total | (3) Likes | (4) Likes | (5) Shares | (6) Shares |
|---|---|---|---|---|---|---|
| Positive | 0.118*** | | 0.101*** | | 0.058 | |
| | (0.043) | | (0.038) | | (0.040) | |
| Happiness | | 0.214* | | 0.208** | | -0.080 |
| | | (0.113) | | (0.100) | | (0.104) |
| $R^2$ | 0.0107 | 0.00518 | 0.00994 | 0.00616 | 0.00306 | 0.000843 |
| Obs. | 697 | 697 | 697 | 697 | 697 | 697 |

*p<.1; **p<.05; ***p<.01.

Table 10: Correlation Between Sentiments and Extremeness. Outcome: Extremeness

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Negative | 0.023** | | | |
| | (0.010) | | | |
| Disgust | | 0.053* | | |
| | | (0.027) | | |
| Positive | | | -0.005 | |
| | | | (0.006) | |
| Happiness | | | | -0.026 |
| | | | | (0.016) |
| $R^2$ | 0.00780 | 0.00544 | 0.000806 | 0.00384 |
| Obs. | 697 | 697 | 697 | 697 |

*p<.1; **p<.05; ***p<.01.

This article explores several aspects of how social media affect political elites by focusing on Chile as a test case. The country has experienced a massive increase in access to mobile internet coverage, which is reflected in the level of penetration of social media in politics. I hypothesized that social media activity increases ideological extremeness among political elites due to two channels. The intrinsic channel posits that politicians move to more extreme positions because negative posts have more circulation on social media. Meanwhile, the extrinsic channel argument is that politicians mirror extremeness among voters, who, due to internet access, are becoming more skeptical about democratic institutions.

I first show that politicians pay considerably more attention to social media as internet coverage improves in their districts. Specifically, if 3G covers a higher share of their constituency, politicians are much more likely to open a Facebook page and interact on social media. Moreover, content analysis shows that Facebook became more of a tool for unidirectional communication than a platform to obtain information about voters' concerns. In this sense, besides the particularities of social media, for example, the possibility of interacting directly with voters, legislators increasingly use these platforms to communicate messages and to get reactions.

The core findings of the paper are that Facebook interactions increase ideological extremeness among political elites. In other words, as politicians spend more time on Facebook, perceiving the feedback of their messages, they move to more extreme positions. When exploring mechanisms, I found evidence of one of the hypothesized channels. Indeed, the descriptive evidence suggests that angry and hostile messages get a better reception on social media than joyful and positive ones. In other words, negativity is rewarded on social media, allowing politicians to reach a broader audience online. Thus, as politicians spend time on social media, politicians may feel "kidnapped' by these type of politicized voters, who are likely scrutinizing their offline behavior. In this sense, the evidence suggest that politicians who heavily engage in Facebook might be afraid of upsetting their online audience in domains outside of social media, consequently moving to ideologically extreme positions.

However, I did not find enough evidence to support the extrinsic channel, as there are no large shifts in public opinion on extremist attitudes that are exclusive of areas with more internet coverage; moreover, even though there is a negative effect of 3G on confidence in democracy —in line with (Guriev et al., 2021) — it happened after politicians opened a Facebook page.

My main contribution to the literature is to establish specific ways in which social media affect political elites in domains beyond the digital world. The few papers that have addressed this relationship have generally focused on how politicians react to the internet or social media within the digital domain (Barberá et al., 2019; Bessone et al., 2019). By building on this scholarship, I also provide several pieces of evidence about how politicians use Facebook in their daily activities, addressing variables such as the penetration, the content, and the sentiment of their posts. Most importantly, I empirically demonstrate that social media increase elite extremeness, implying that social media could have a real impact in the real world.

In addition, my article relates to the discussion of whether politicians lead or follow the public (Lenz, 2012), in this case, regarding radicalism. The evidence presented here suggests that increases in ideological extremism are not driven by either the median voter or by a significant portion of supporters outside social media; on the contrary, a relatively small group of politicized and active social media users have the capacity to capture the attention of political elites, eventually altering their behavior.

Likewise, my results speak to the understanding of polarization in the global south. In the last few years, Latin America has experienced increased political polarization. In countries such as Colombia, Brazil, Peru, and Chile, the second round of the presidential elections has included candidates who lean toward the extremes, lacking any consistent political majority to govern effectively. The evidence provided here sheds light on a plausible explanation for this phenomenon, as social media and the internet reward specific types of leadership. In this sense, it will not be surprising to witness countless politicians chasing "likes" on social media in the coming years.

The fact that extremeness is rewarded on social media highlights the importance of intermediaries in the political discussion: that is, journalists and editors with a commitment to fighting misinformation and filtering certain types of speech. However, demagogues around the world attack the intermediaries, claiming that social media allow a more genuine contact with the people, as opposed to an allegedly corrupt traditional media;[32] In this paper, I show that the reality is entirely the opposite: it is the absence of intermediaries that makes social media a space where extremeness is rewarded and which ends up lighting the flames of polarization.

This study opens up a series of new questions for future research. For example, an interesting question is how exposure to the internet affects political attitudes in developing or middle-income countries. In this paper, I show the impact of 3G on only two outcomes related to the support of democracy and elections. However, it is plausible that the internet also increases support for more "progressive" initiatives - especially among young people - since voters could be exposed to arguments from more developed countries. Nevertheless, it is also possible that access to information gives better arguments to groups on the fringes of the political spectrum, allowing them to persuade more people of their point of view.

A second area is to continue exploring how politicians interact on Facebook, Twitter, In-

[32] An example is Franco Parisi, a candidate who, in the 2021 Chilean presidential election, obtained a non-negligible 12.8% of the vote. He built his campaign entirely through social media, as he was not allowed to enter the country.

stagram, and TikTok, and the impact on myriad outcomes. In this paper, I heavily focused on Facebook, given that my dataset started in 2010. However, nowadays, politicians rely heavily on Twitter and Instagram to talk about national politics and TikTok to try to be intimate and funny. In this sense, qualitative research could be valuable for exploring the multiple ways they use these platforms. Do politicians quantify the success of a given post? How sophisticated are they in analyzing impact indicators? How important is this information compared to other feedback they could receive, such as polling data or personal contact? Answering these questions could shed light on the multiple ways social media affect elite behavior.

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# Appendix: Additional Tables and figures

Figure A1: Media Consumption in Chile 2018-2020

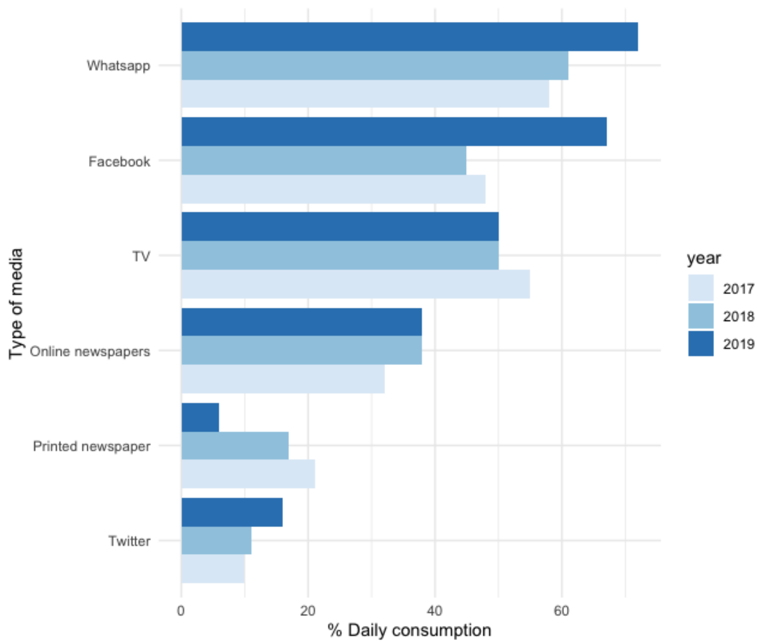



Table A1: Population Covered by 3G and 4G

| Year | Population covered by 3G + 4G | Share 3G + 4G |
|---|---|---|
| 2009 | 638,787 | 0.04 |
| 2010 | 1,445,875 | 0.08 |
| 2011 | 3,154,995 | 0.18 |
| 2012 | 4,983,888 | 0.29 |
| 2013 | 6,366,120 | 0.36 |
| 2014 | 9,155,723 | 0.52 |
| 2015 | 10,283,244 | 0.57 |
| 2016 | 13,215,139 | 0.73 |
| 2017 | 16,322,988 | 0.88 |
| 2018 | 18,153,905 | 0.97 |
| 2019 | 18,464,155 | 0.97 |

The roll-out of 4G started in 2015.

Table A2: Robustness Check of Effects 3G Coverage on Facebook Activity (Two Treatment Leads)

| | (1)<br>Page | (2)<br>Likes | (3)<br>Total | (4)<br>Shares |
|---|---|---|---|---|
| 3G Share | 0.447** | 1.371** | 1.414** | 0.400 |
| | (0.213) | (0.558) | (0.611) | (0.378) |
| 3G Share (t+1), | -0.037 | 0.199 | 0.158 | -0.209 |
| | (0.122) | (0.602) | (0.663) | (0.466) |
| 3G Share (t+2), | 0.222 | 0.803 | 0.909 | 0.570 |
| | (0.157) | (0.640) | (0.695) | (0.453) |
| $R^2$ | 0.761 | 0.804 | 0.804 | 0.802 |
| Obs. | 579 | 579 | 579 | 579 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. Adjusted models control for log of population, log of income, urban status, average age, vote share, and political coalition. See table SF3 in Supplementary Material F for a complete table including the control variables.

Table A3: Effects 3G Coverage on Facebook Activity (Two Treatment Lags)

| | (1)<br>Page | (2)<br>Likes | (3)<br>Total | (4)<br>Shares |
|---|---|---|---|---|
| 3G Share | 0.501** | 0.507 | 0.615 | -0.103 |
| | (0.201) | (0.667) | (0.729) | (0.432) |
| 3G Share (t-1) | 0.080 | 0.905 | 0.976 | 0.753* |
| | (0.144) | (0.623) | (0.682) | (0.384) |
| 3G Share (t-2) | 0.162 | 1.443* | 1.515 | 0.927 |
| | (0.203) | (0.847) | (0.936) | (0.671) |
| Politician*District FE | Yes | Yes | Yes | Yes |
| Region*Year FE | Yes | Yes | Yes | Yes |
| Adjusted | Yes | Yes | Yes | Yes |
| $R^2$ | 0.801 | 0.807 | 0.808 | 0.809 |
| Obs. | 462 | 462 | 462 | 462 |

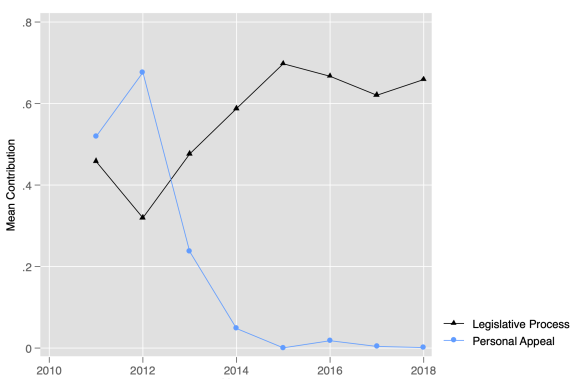
*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. Adjusted models control for log of population, log of income, urban status, average age, vote share, and political coalition. See table SF4 in Supplementary Material F for a complete table including the control variables.

Table A4: Effects of 4G Coverage on Facebook Activity

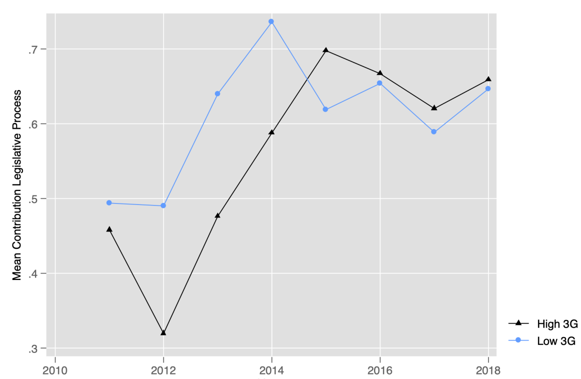
| | (1) Likes | (2) Likes | (3) Likes | (4) Likes |
|---|---|---|---|---|
| Share 4G | -0.320 | -1.331 | -1.324 | -0.283 |
| | (0.258) | (0.948) | (1.054) | (0.829) |
| $R^2$ | 0.797 | 0.815 | 0.814 | 0.822 |
| Obs. | 466 | 466 | 466 | 466 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district-year level. The sample size for these regressions correspond to politician*years in the 2013-2017 congressional session. All models include politician*district and region*year fixed effects. Models are adjusted for 3G coverage, log of population, log of income, urban status and average age. Given that I am including one congressional session, I could not include vote share and political coalition due to collinearity. See table SF5 in Supplementary Material F for a complete table including the control variables.

Figure A2: Mean Contribution Topics Facebook Posts




(a) High 3G




(b) By 3G Status

Figure A3: Histograms Extremeness Measure by Year

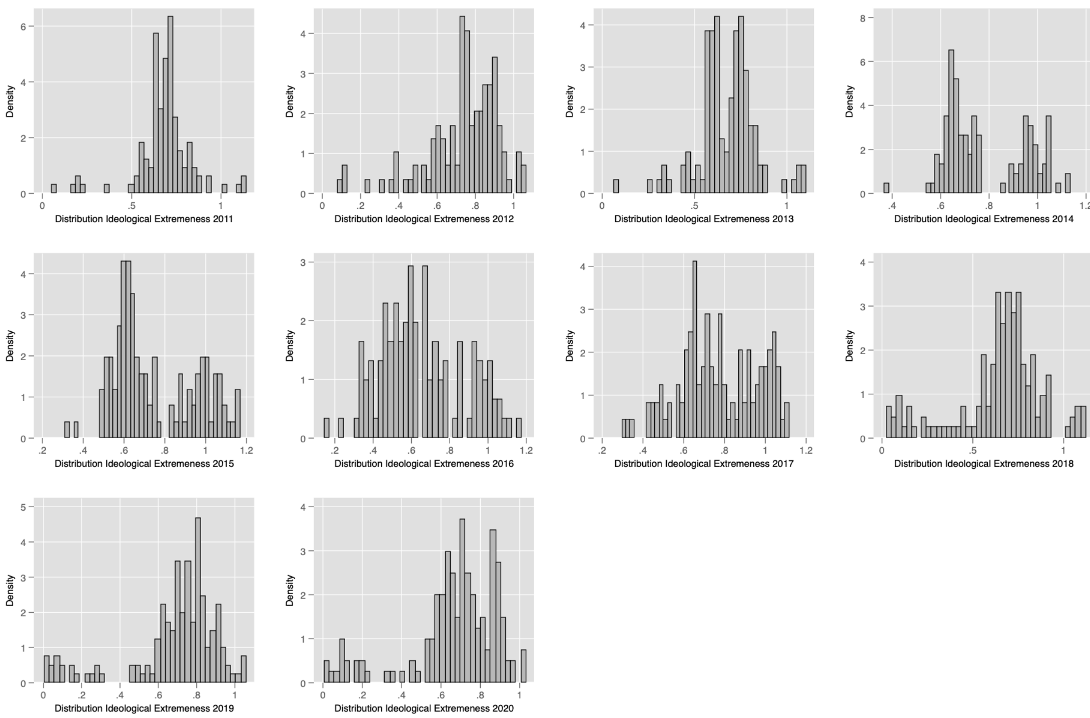



Table A5: Average Extremism by Year

| Year | Average Extremism |
|---|---|
| 2011 | 0.69 |
| 2012 | 0.74 |
| 2013 | 0.68 |
| 2014 | 0.79 |
| 2015 | 0.75 |
| 2016 | 0.66 |
| 2017 | 0.78 |
| 2018 | 0.65 |
| 2019 | 0.69 |
| 2020 | 0.67 |

Table A6: Most Extreme Legislators by Year

| Most extreme legislator | Party | Year | Who governed? |
|---|---|---|---|
| Hugo Gutierrez | Communist | 2011 | Right |
| Lautaro Carmona | Communist | 2012 | Right |
| Hugo Gutierrez | Communist | 2013 | Right |
| German Becker | National Renewal | 2014 | Center-Left |
| Gustavo Hasbún | Independent Democratic Union | 2015 | Center-Left |
| Gustavo Hasbún | Independent Democratic Union | 2016 | Center-Left |
| Jorge Ulloa | Independent Democratic Union | 2017 | Center-Left |
| Claudia Mix | Comunes | 2018 | Right |
| Florcita Alarcón | Humanist | 2019 | Right |
| Pamela Jiles | Humanist | 2020 | Right |

Table A7: Bills 2011-2019

| Issues | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Science and Technology | 5.7 | 0.2 | 7.6 | 2.1 | 0.9 | 1.1 | 1.1 | 0.9 | 0.4 | 1.8 | 1.9 |
| Constitution | 7.8 | 5.7 | 1.7 | 10.9 | 3.4 | 1.3 | 4.1 | 3.4 | 4.9 | 5.5 | 5.1 |
| Defense | 0.6 | 4.8 | 3.4 | 0.2 | 2.1 | 7.3 | 9.7 | 5.2 | 7.7 | 7.0 | 5.2 |
| Economy | 9.9 | 9.5 | 0.5 | 0.0 | 8.9 | 7.2 | 3.3 | 9.2 | 8.2 | 17.8 | 7.2 |
| Education | 1.9 | 4.6 | 2.7 | 28.5 | 21.2 | 10.9 | 28.4 | 9.8 | 3.3 | 5.4 | 11.6 |
| Homeland | 10.1 | 9.0 | 17.6 | 3.1 | 1.1 | 0.1 | 3.3 | 0.1 | 0.9 | 0.1 | 4.0 |
| Fiscal policy | 39.9 | 41.7 | 24.9 | 40.5 | 32.2 | 28.2 | 21.2 | 36.9 | 30.8 | 19.5 | 30.4 |
| Infraestructure | 0.0 | 1.1 | 0.3 | 0.0 | 13.1 | 12.5 | 4.2 | 18.8 | 15.0 | 23.3 | 9.5 |
| Fishing | 1.0 | 11.5 | 0.0 | 0.8 | 1.1 | 0.0 | 9.5 | 0.1 | 6.7 | 0.8 | 3.5 |
| Health | 5.7 | 3.7 | 6.8 | 0.0 | 3.3 | 4.1 | 2.5 | 3.7 | 0.7 | 0.6 | 3.0 |
| Labor | 2.7 | 1.5 | 0.9 | 0.4 | 2.0 | 5.5 | 1.8 | 3.0 | 4.0 | 6.1 | 3.6 |
| Other | 14.8 | 6.9 | 33.7 | 13.4 | 10.9 | 21.7 | 11.0 | 8.9 | 17.4 | 12.2 | 15.2 |
| Total | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |

**Counts of words**

# The Internet, Social Media, and Elite Extremeness: Evidence from Chile

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## Contents

# 1 Supplementary Material A: Challenges to Identification

Certainly, 3G roll out in Chile was not randomly assigned, as more covered places are likely more populated and urban compared to less covered ones. In this sense, the mere comparison among localities will, most likely, yield biased results. To address this potential endogeneity problem, I applied several statistical techniques for observational data, with the purpose of approaching causal identification as best as possible.

First, I remind the reader that the two-way fixed effects model adjust for politician heterogeneity and for region-specific time trends. This implies that differences across politicians, and events affecting particular regions are already accounted for, as the source of the variation is within-politician over time. In this sense, any potential effect implies that a given politician changed their behavior concurrently with increases in 3G access.

Second, I estimate all the models with and without time-variant demographic and political controls. If the hypothesized effects are robust, I expect that the coefficients will not change dramatically after the inclusion of such controls; if a coefficient goes to zero it would mean that the independent variable of interest —for example, 3G internet— was capturing the effect of one of the included covariates.

Third, I included lead versions of the independent variable of interest in all the relevant models. If an effect exists, then the coefficient of the lead variables —that is, the same independent variable in future time— should be zero.

Finally, I conducted an instrumental variable specification (see Appendix E for a longer discussion about the validity of this estimator) to test hypotheses 4, using 3G access as an instrument of Facebook activity.

None of this strategies by itself would completely assure the validity of the causal estimates. However, finding the same result in all these different empirical strategies, regardless of the specification, increases the credibility of the results.

# 2 Supplementary Material B: Data Building

To build the dataset, I started with the shape files provided by Collin's Bartholomew, consisting in 1*1 grid cells indicating 3G coverage. Then, I follow the exact procedure done by Guriev, Melnikov, and Zhuravskaya 2021, described in the README file located in https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/SMUOF7. Basically, I multiply the data indicating presence of absence of 3G coverage by the population density in a 1*1 grid cell in all the Chilean territory. For the 2010-2014 period, I use the population density of 2010 according with the NASA dataset; for the years beyond 2015, I used the density of 2015.

The resulting data shows how many people is covered in by 3G in Chile. Then, I sum up the number of people covered by municipality or district; finally, I divide number of people covered by the population, resulting in the share of Chileans covered by 3G in the corresponding administrative unit. Based on this variable, I created four different datasets:

1. The first dataset is at the politician*year level, which includes share of 3G coverage, Facebook activity measures and the extremeness measure. I manually constructed the dataset at the politician-year level; then, I merged it with the 3G variable, the extremeness variable and the Facebook variables. Before 2017, there were two legislators per district, meaning that the treatment variable —share of district population with access to 3G— covered two politicians. After 2017, there was a reform of the electoral system, which increased district size with a variable number. Thus, there were between five and eight politicians per district.

2. The second dataset is at the politician*municipality*year level, which was used to analyze whether politicians responded more to municipalities with higher access to 3G within a district. Here, the treatment data varied by municipality*year.

3. Thirdly, for 2019 —the year of the crisis—, I created a data set at the politician-day

level. The 3G variable was constructed at the district level.

4. Finally, I merged the 3G data at the municipality level to polling data from Lapop, to study the impact of access to internet on voter's support for democracy.

Along the paper, I will explain to the reader which data set I am using for a given analysis.

# 3 Supplementary Material C: Within District Analysis

As an additional test to relate Facebook attention and 3G coverage, I follow the logic of Bessone et al. 2019, who exploit the presence of municipalities within districts with different levels of access to 3G coverage. This model allows analyzing whether, within a district, politicians paid more attention to municipalities with higher 3G coverage. Put another way, it allows studying whether politicians adopt more specific strategies based on micro-level differences in internet coverage. To this end, I set up the dataset at the municipality*year level, exploiting variation of 3G coverage across municipalities within districts.

As an outcome, I use whether a politician mentioned the name of municipality $m$ in a Facebook post in a given year and the number of times that such municipality was mentioned: $log(1 + frequency)$. I estimate two different specifications, which exploits different sources of variation:

$$Y_{mi} = \alpha + \eta(3G)_m + \gamma_i + \epsilon \tag{1}$$

This equation leverages cross-sectional variation in 3G across municipalities. The treatment $3G$ indicates the share of 3G in a municipality, while $\gamma$ accounts for politician fixed-effects. The source of variation is across municipalities, controlling for politician in a given year. The purpose is to exploit between municipality variation in 3G, analyzing whether politicians pay more attention to places with higher 3G, and to see how this relationship evolves. I estimated these models separately from 2015 and on, as more than half of politicians had a Facebook page in such year.

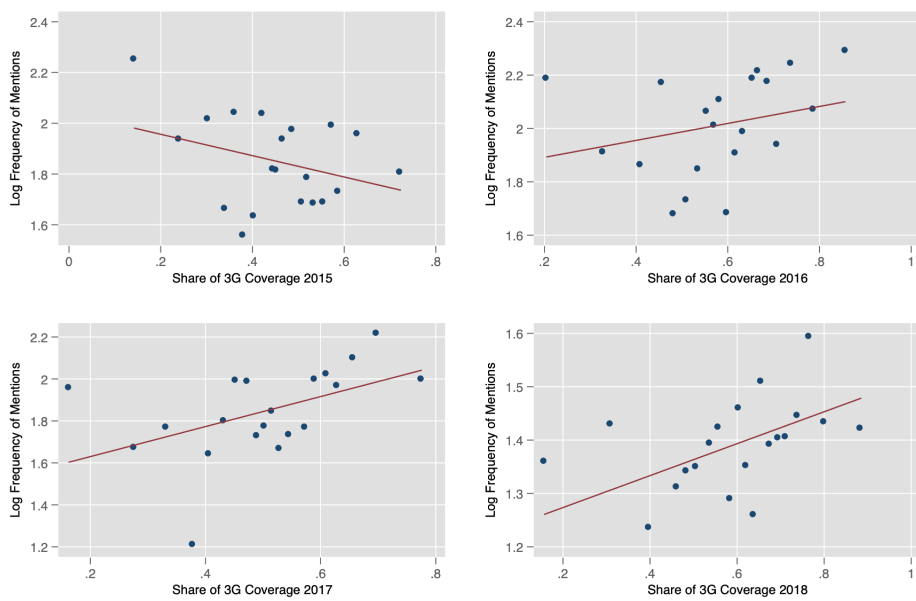
I estimate a second model, exploiting over time variation by municipality, adjusting by politician*municipality. This allows to see whether changes in 3G by municipality correlates with higher levels of attention to that same locality:

$$Y_{imrt} = \alpha + \zeta(3G)_{mrt} + \gamma_{imrt} + \lambda_{rt} + \epsilon \tag{2}$$

Where the dependent variable is defined for politician $i$, municipality $m$, in the region $r$, at time $t$. In equation 3, the parameter of interest is $\zeta$, the effect of increases on 3G coverage on changes in municipality mentions. Moreover, $\gamma_{imry}$ accounts for politician*municipality fixed effects + and $\lambda_{ry}$ adjust for regional time trends.

## Results

Figure SC1: Bin Scatters Municipality Mentions and Share 3G




The scatter plots include politician fixed-effects, and controls for for log of population, log of income, urban status, average age.

Results show that it is unclear whether politicians distinguish between municipalities with higher or lower access to the internet within districts. Indeed, figure SC1 shows the

Table SC1: Municipality Mentions and Share 3G

| | (1) Log Mentions 2018 | (2) Log Mentions 2017 | (3) Log Mentions 2016 | (4) Log Mentions 2015 |
|---|---|---|---|---|
| Share 3G | 0.299 | 0.710** | 0.304 | -0.407 |
| | (0.209) | (0.311) | (0.327) | (0.310) |
| Adjusted | Yes | Yes | Yes | Yes |
| $R^2$ | 0.654 | 0.750 | 0.732 | 0.822 |
| Obs. | 1359 | 394 | 277 | 249 |

*p<.1; **p<.05; ***p<.01. All models include politician fixed effects. Adjusted models control for log of population, log of income, urban status, average age, vote share, and political coalition.

cross-sectional analysis by year, including politician fixed effects and a set of controls (table SC1 show the corresponding table with the regression coefficients). We see that the slope of the regression coefficient becomes positive over time, suggesting that politicians increasingly pay more attention to municipalities with higher internet access. However, only for 2017, the slope is statistically different from zero — see table SC1.[1] Table SC2 presents the models which exploits the over time variation of municipalities. Again, we observe a positive effect, but none of the models are statistically significant.

Taken together, these results suggest that even though district level increase in 3G access increments politicians' attention to social media, it is unclear whether politicians pay more attention to municipalities with higher access to 3G within their districts.

[1]Note that starting in the 2017 parliamentary election there was an increase in district size, as each district incorporated more municipalities. That explains the increase in sample size in 2018 described in table SC1.

Table SC2: Effects of 3G at the Municipal Level on Mentions

| | (1) One Mention | (2) One Mention | (3) Log Mentions | (4) Log Mentions |
|---|---|---|---|---|
| Share 3G | 0.186 | 0.173 | 0.826 | 0.763 |
| | (0.209) | (0.207) | (0.596) | (0.579) |
| Adjusted | No | Yes | No | Yes |
| $R^2$ | 0.584 | 0.587 | 0.750 | 0.753 |
| Obs. | 1075 | 1075 | 1075 | 1075 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the municipality level. The sample size includes politician*years*municipalities between 2015 and 2018, period where at least half of politicians had a Facebook page. All models include politician*municipality and region*year fixed effects. Adjusted models control for log of population, log of income, urban status, average age, vote share, and political coalition.

# 4 Supplementary Material D: Topic Modeling

Table SD1: Top 20 Words Policy Topic among High 3G

| Policy | | | |
|---|---|---|---|
| **5 Topics** | **10 Topics** | **15 Topics** | **20 Topics** |
| Proyecto | Proyecto | Proyecto | Proyecto |
| Vecinos | Vecinos | Vecinos | Vecino |
| Gobierno | Gobierno | Gobierno | Gobierno |
| Trabajo | Comuna | Comuna | Comuna |
| Comuna | Trabajo | Trabajo | Trabajo |
| Pais | País | País | País |
| Años | Años | Años | Años |
| Nacional | Nacional | Nacional | Nacional |
| Ley | Región | Región | Región |
| Región | Ley | Ley | Ley |
| Educación | Educación | Educación | Cámara |
| Salud | Cámara | Cámara | Educación |
| Cámara | Salud | Sector | Sector |
| Reunión | Sector | Salud | Presidente |
| Nueva | Presidente | Reunión | Salud |
| Comisión | Reunión | Equipo | Nueva |
| Diputados | Nueva | Presidente | Reunión |
| Nuevo | Equipo | Nueva | Equipo |
| Parte | Diputados | Diputados | Vida |
| Sector | Nuevo | Nuevo | Diputados |

As robustness check, I ran the topic model algorithm with different number of topics: 20, 15, 10 and 5. In each of the iterations, the results are very similar to the ones presented in the results section: among the high 3G group, there are two different topics that predominate in the period, which are distinguishable from each other. I called the first topic "Appeal" because its main words have the purpose to directly appeal voters to get in touch with politicians. The second topic —defined as "Policy— alludes to the legislative process, and became more prevalent over time. This suggests that communication on social media became more unidirectional. Table SD1 shows the top 20 words of the Policy topic with varying number of $k$ among the high 3G group, in the original language. Meanwhile, table SD2 show the top 20 words of the Appeal topic in the high 3G group. Both tables confirms that the themes are clearly identified regardless of the total number topics defined previously.

Table SD2: Top 20 Words Appeal Topic among High 3G

| **Appeal** | | | |
|---|---|---|---|
| **5 Topics** | **10 Topics** | **15 Topics** | **20 Topics** |
| Mejor | Mejor | Mejor | Mejor |
| Gobierno | Esfuerzo | Esfuerzo | Esfuerzo |
| Esfuerzo | Siempre | Siempre | Siempre |
| Ayudar | Ver | Ver | Ayudar |
| Siempre | Gente | Ayudar | Ver |
| Concepción | Ayudar | Gente | Piensas |
| Haré | Piensas | Piensas | Contáctame |
| Piensas | Contáctame | Contáctame | Haré |
| Contáctame | Haré | Haré | Apoyarte |
| Ver | Apoyarte | Apoyarte | Concepción |
| Atentamente | Concepción | Concepción | Sur |
| Apoyarte | Gobierno | Online | Gobierno |
| Gente | Online | Gobierno | Atentamente |
| Apoyo | Bío-Bío | Bío-Bío | Bío-Bío |
| Chiguayante | Atentamente | Atentamente | Online |
| Bío-Bío | Ley | Ley | Ley |
| Revisar | Chiguayante | Chiguayante | Chiguayante |
| Diputados | Sandra | Sandra | Dipuatdos |
| Online | Hermann | Hermann | Sandra |
| Ley | Diputados | Vida | Hermann |

The subsequent tables shows the two main predominant topics among the low 3G group. The first topic is clearly related to policy, whose top 20 words are displayed in table SD3.

Finally, table SD4 shows the second most relevant topic according to the model. As explained the results section, this is difficult to identify, although most of their keywords relate to policy, such as "ley" and "proyecto". In this sense, among the low 3G group, it seems that the only one relevant topic, which is show in table SD3.

Table SD3: Top 20 Words Policy Topic among Low 3G

| **Policy** | | | |
|---|---|---|---|
| **5 Topics** | **10 Topics** | **15 Topics** | **20 Topics** |
| Proyecto | Proyecto | Proyecto | Proyecto |
| Gobierno | Gobierno | Gobierno | Gobierno |
| Vecinos | Vecinos | Ley | Ley |
| Región | Ley | Vecinos | Vecinos |
| Ley | Región | Región | Región |
| Comuna | País | Comuna | Comuna |
| Años | Años | Años | Años |
| Ahora | Comuna | País | Trabajo |
| País | Ahora | Ahora | País |
| Trabajo | Trabajo | Trabajo | Ahora |
| Nacional | Educación | Nacional | Nacional |
| Educación | Nacional | Educación | Educación |
| Diputados | Diputados | Diputados | Diputados |
| Salud | Salud | Salud | Salud |
| Personas | Personas | Vida | Personas |
| Parte | Vida | Personas | Vida |
| Nuevo | Alcalde | Regional | Parte |
| Vida | Nuevo | Parte | Regional |
| Años | Regional | Nuevo | Nuevo |
| Todas | Parte | Alcalde | Alcalde |

Table SD4: Top 20 Words Second Most Relevant Topic among Low 3G

| Undistinguishable | | | |
|---|---|---|---|
| **5 Topics** | **10 Topics** | **15 Topics** | **20 Topics** |
| Ley | Ley | Ley | Ley |
| Proyecto | Proyecto | Serena | Serena |
| Comisión | Serena | Proyecto | Proyecto |
| UDI | Reunión | Reunión | Reunión |
| Reforma | Rumbo | Rumbo | Rumbo |
| Serena | Modifica | Comisión | Coquimbo |
| Reunión | Comisión | Coquimbo | Comisión |
| Arica | Adultos | Constitución | Adultos |
| Nuñez | Sala | Adultos | Vicuña |
| Cámara | Votar | Modifica | Constitución |
| Linares | JJVV | Vicuña | Modifica |
| Rumbo | Constitución | Sala | Sala |
| Concejal | Club | Club | JJVV |
| Coquimbo | Establece | JJVV | Club |
| Maule | Actividades | Objeto | Votar |
| Gutierrez | Distrital | Votar | Siguientes |
| Candidatos | Vicuña | Siguientes | Objeto |
| Sala | Coquimbo | Establece | Establece |
| Entrevista | Vecinos | Proyectos | Actividades |
| Bachelet | Objeto | Actividades | Discutir |

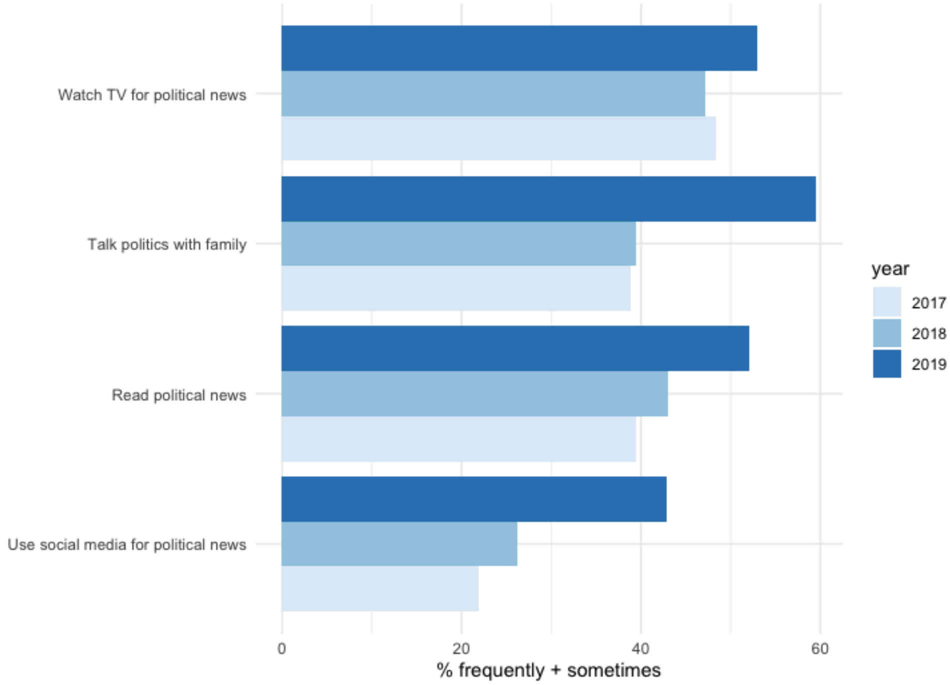
# 5 Supplementary Material E: The October Revolt

In this appendix, I want to analyze the role of social media in the context of an acute and unexpected political crisis, which happened in October 19th, 2019. That evening, a wave of protests motivated by an increase in subway fares led to widespread street violence in Santiago, Chile's capital, including an attack on the subway system, arson, looting, and generalized vandalism. In the following days, hundreds of thousands of people took the streets to protest for what has been interpreted as discontent with inequality in different aspects of social life.

I want to highlight three elements of this crisis. First, for several months, there was an overwhelming amount of political information that flooded the media. According to polling data from CEP, there was a substantial increase in the percentage of people who consumed political information frequently (see figure E1). Second, the political discussion became very belligerent and polarized, partly because of the unprecedented levels of street violence. Third, Chileans heavily use social media as a source of political information. Indeed figure E1 shows that the share of people who used Facebook for political news increased by 17 percentage points, whereas TV consumption increased in a lesser degree.

The Chilean crisis of 2019 represents a natural experiment about an unusual level of attention to politics among a large group of the population, and an important shift towards social media consumption. Thus, it is a good scenario to analyze attention to social media among political elites. As the crisis happened in a national scale, it is unclear whether politicians in districts with higher access to 3G would react differently than the ones in less connected districts.

Figure E1: Media and Political Consumption Chile December 2017 - 2019 (source: CEP)



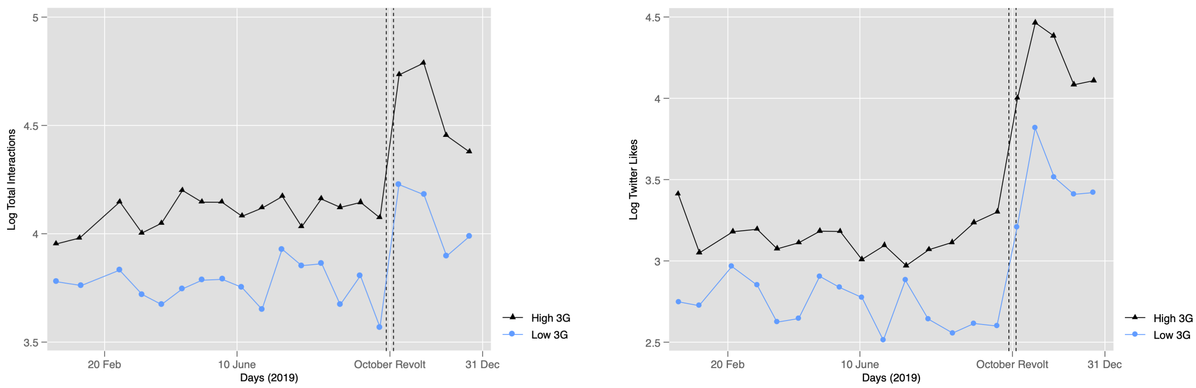

## Data, Measures and Empirical Strategy

To analyze whether access to the internet impacts attention during the crisis, I create a data set at the politician-day level for 2019, exploiting the significant shock that occurred on October 18th. I follow the logic of an event study, analyzing, in the first place, how such events impact attention and then estimating the impact of internet access. In addition to the Facebook measures used previously, I added outcomes scrapped from Twitter, such as $log(1 + retweets)$ and $log(1 + likes)$. By looking at the daily average of Facebook and Twitter interactions in figure E2, we can tell that there was a large increase in the week of the events.

The statistical model can be described as follows:

$$Y_{id} = \alpha + \tau_1(revolt)_d + \tau_2(3G)_i + \tau_3(3G * revolt)_i + \gamma_i + \epsilon \quad (3)$$

Figure E2: Daily Total Interactions Facebook and Twitter 2019




(a) Facebook (b) Twitter

Where activity on social media of politician $i$ on the day $d$ is regressed on an indicator variable equal to one after the revolt, zero otherwise, and on an indicator of being above the median in access to 3G. The term $\gamma$ accounts for politician fixed effects. The parameter $\tau_3$ is the main quantity of interest, as it represents the difference in social media interactions between high and low access to 3G.[2] Given that I adjust for politician fixed-effects, I cannot control for district-level variables because they do not change over time. Due to the data structure, I will be able to present more leads and lags to confirm the validity of the results.

## Results

Table E1 shows the effect of the revolt on Twitter interactions at different levels of 3G access. Clearly, we see that the increase in likes and retweets was 34% higher in both cases among politicians of high 3G districts compared to low 3G (see the interaction coefficient in column 2 of table E1), a very substantial amount. Regarding Facebook, we also see a significant effect (see table E2). figure E3 shows a visualization of these results, as it calculates the average daily interactions net of politician fixed effects. As we see, the increase in Facebook

[2]I could not include a continuous variable for 3G access because it varies at the district level, and therefore is colinear to politician fixed-effects.

and Twitter interactions was considerably higher for politicians with more internet access.

Table E1: Event Study October Revolt (Twitter)

| | (1) Log Retweet | (2) Log Retweet | (3) Log Likes | (4) Log Likes |
|---|---|---|---|---|
| Revolt | 0.801*** | 0.570*** | 0.842*** | 0.615*** |
| | (0.092) | (0.140) | (0.096) | (0.141) |
| Share 3G | | 0.305*** | | 0.304*** |
| | | (0.023) | | (0.024) |
| Revolt*Share 3G | | 0.343* | | 0.337* |
| | | (0.181) | | (0.186) |
| $R^2$ | 0.637 | 0.638 | 0.694 | 0.695 |
| Obs. | 12597 | 12597 | 12597 | 12597 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*days for 2019.

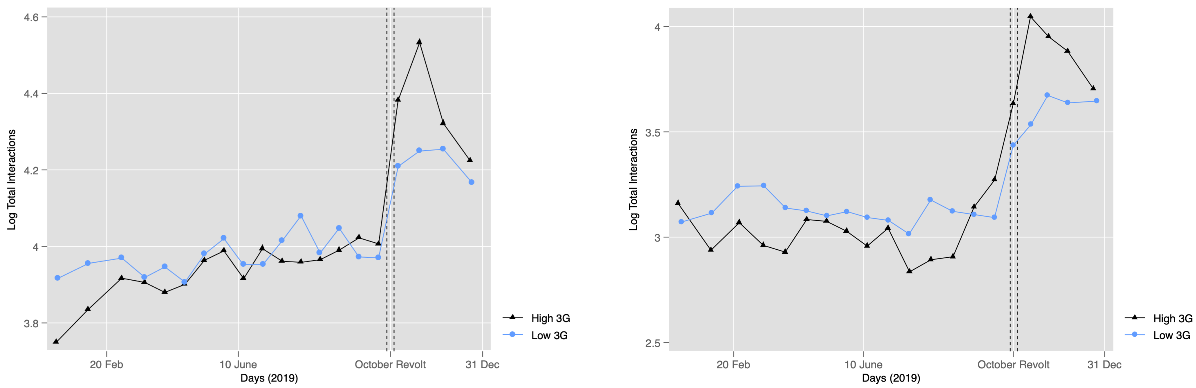
Table E2: Event Study October Revolt (Facebook)

| | (1) Log Total | (2) Log Total | (3) Log Shares | (4) Log Shares |
|---|---|---|---|---|
| Revolt | 0.414*** | 0.314*** | 0.405*** | 0.260*** |
| | (0.041) | (0.055) | (0.044) | (0.059) |
| High 3G | | 0.951*** | | 1.109*** |
| | | (0.015) | | (0.016) |
| Revolt*High 3G | | 0.180** | | 0.259*** |
| | | (0.080) | | (0.085) |
| $R^2$ | 0.521 | 0.522 | 0.428 | 0.429 |
| Obs. | 24119 | 24119 | 24119 | 24119 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*days for 2019.

When analyzing pre-trends, table E4 shows the revolt coefficient, adding pre and post trends, defined as dummy variables indicating five, ten and fifteen days before and after the event. For Facebook (panel a), we see that for both high and low 3G, the effect appears immediately after the revolt, although it is higher for the former group. In the case of Twitter

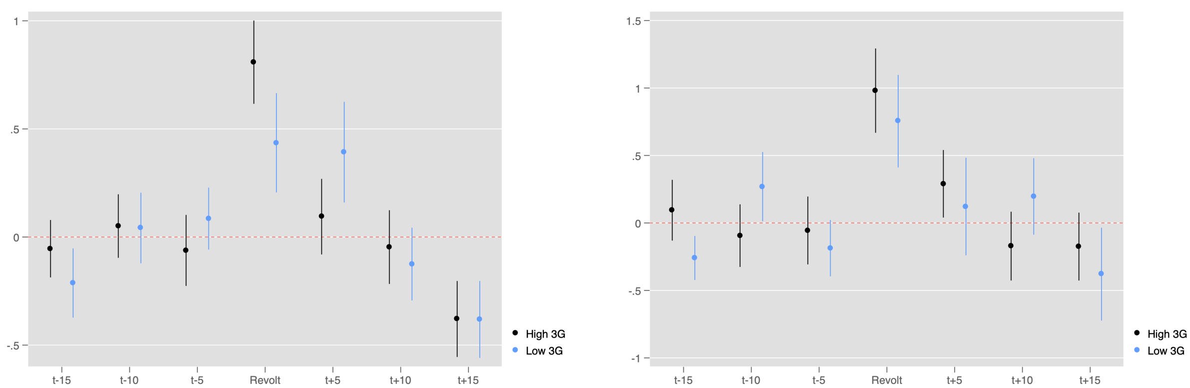
Figure E3: Daily Total Interactions Facebook and Twitter 2019 (Politician Fixed Effects)




(a) Facebook (b) Twitter

(panel b), we see a substantive effect of the revolt, for both types of legislators. Probably, Twitter interactions —as opposed to Facebook— are more affected by national events and less influenced by district-level access to the internet.

Figure E4: Coefficient plot October Revolt Twitter and Facebook




(a) Facebook (b) Twitter

Overall, we see that the October revolt caused a very substantial increase in social media elite interactions. In the case of Facebook, there is a marked difference between high and low access to the internet, suggesting that elite attention —even in a national crisis— is conditioned by voter's access to the internet.

# 6 Supplementary Material F: Complete Tables

Table SF1: Effects of 3G Coverage on Facebook Activity

| | (1) Pages | (2) Pages | (3) Likes | (4) Likes | (5) Total | (6) Total | (7) Shares | (8) Shares |
|---|---|---|---|---|---|---|---|---|
| Share 3G | 0.462* | 0.453** | 1.570*** | 1.414** | 1.674*** | 1.505** | 0.585 | 0.436 |
| | (0.232) | (0.219) | (0.536) | (0.594) | (0.585) | (0.662) | (0.390) | (0.404) |
| Vote Share | | 0.255 | | -0.813 | | -0.975 | | -1.440 |
| | | (0.323) | | (1.066) | | (1.222) | | (1.059) |
| Right | | -0.209 | | -0.167 | | -0.251 | | -0.038 |
| | | (0.164) | | (0.454) | | (0.506) | | (0.218) |
| Ind. | | -0.258*** | | -0.629*** | | -0.763*** | | -0.434*** |
| | | (0.080) | | (0.173) | | (0.188) | | (0.093) |
| Left | | -0.150 | | 0.096 | | -0.065 | | -0.168 |
| | | (0.107) | | (0.267) | | (0.295) | | (0.178) |
| Log pop | | -0.091 | | -0.123 | | -0.091 | | -0.006 |
| | | (0.120) | | (0.394) | | (0.450) | | (0.303) |
| Log income | | -0.061 | | -0.468 | | -0.509 | | -0.347 |
| | | (0.102) | | (0.322) | | (0.360) | | (0.237) |
| Age | | 0.037** | | 0.062 | | 0.078 | | 0.026 |
| | | (0.016) | | (0.050) | | (0.054) | | (0.028) |
| Urban | | 0.326 | | 1.010 | | 1.057 | | 0.485 |
| | | (0.270) | | (0.944) | | (1.046) | | (0.610) |
| $R^2$ | 0.755 | 0.760 | 0.781 | 0.784 | 0.782 | 0.785 | 0.781 | 0.786 |
| Obs. | 826 | 814 | 826 | 814 | 826 | 814 | 826 | 814 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. The omitted category of political coalition is center.

# References


Bessone, Pedro, et al. 2019. "Internet Access, Social Media, and the Behavior of Politicians: Evidence from Brazil".

Table SF2: Effects of 3G Coverage on Facebook Activity (One lead)

| | (1) Pages | (2) Likes | (3) Total | (4) Shares |
|---|---|---|---|---|
| 3G Share | 0.510** | 1.379** | 1.469** | 0.418 |
| | (0.210) | (0.531) | (0.591) | (0.352) |
| 3G Share (t+1) | 0.006 | 0.273 | 0.253 | -0.093 |
| | (0.147) | (0.582) | (0.643) | (0.449) |
| Vote Share | 0.240 | -0.577 | -0.772 | -1.373 |
| | (0.310) | (1.029) | (1.189) | (1.125) |
| Right | -0.229 | -0.206 | -0.293 | -0.076 |
| | (0.154) | (0.375) | (0.407) | (0.193) |
| Ind. | -0.277** | -0.550** | -0.702*** | -0.479*** |
| | (0.104) | (0.223) | (0.249) | (0.176) |
| Left | -0.160 | 0.323 | 0.143 | -0.181 |
| | (0.125) | (0.303) | (0.333) | (0.230) |
| Log pop | -0.177 | 0.002 | -0.041 | -0.261 |
| | (0.290) | (1.021) | (1.126) | (0.679) |
| Log income | 0.042 | -0.192 | -0.244 | -0.502 |
| | (0.187) | (0.640) | (0.696) | (0.337) |
| Urban | 0.307 | 0.644 | 0.748 | 0.515 |
| | (0.338) | (1.120) | (1.222) | (0.703) |
| Age | 0.046* | 0.085 | 0.097 | 0.018 |
| | (0.024) | (0.075) | (0.081) | (0.038) |
| $R^2$ | 0.773 | 0.807 | 0.808 | 0.806 |
| Obs. | 716 | 716 | 716 | 716 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. The omitted category of political coalition is center.

Table SF3: Effects of 3G Coverage on Facebook Activity (Two leads)

| | (1) Page | (2) Likes | (3) Total | (4) Shares |
|---|---|---|---|---|
| 3G Share | 0.447** | 1.371** | 1.414** | 0.400 |
| | (0.213) | (0.558) | (0.611) | (0.378) |
| 3G Share (t+1) | -0.037 | 0.199 | 0.158 | -0.209 |
| | (0.122) | (0.602) | (0.663) | (0.466) |
| 3G Share (t+2) | 0.222 | 0.803 | 0.909 | 0.570 |
| | (0.157) | (0.640) | (0.695) | (0.453) |
| Vote Share | 0.278 | -0.334 | -0.519 | -1.247 |
| | (0.301) | (1.012) | (1.172) | (1.201) |
| Right | -0.075 | 0.058 | 0.007 | -0.101 |
| | (0.129) | (0.354) | (0.385) | (0.279) |
| Ind. | -0.151 | -0.272 | -0.358 | -0.309 |
| | (0.111) | (0.286) | (0.313) | (0.204) |
| Left | -0.046 | 0.616 | 0.493 | 0.022 |
| | (0.136) | (0.383) | (0.422) | (0.296) |
| Log pop | -0.143 | 0.052 | 0.029 | -0.217 |
| | (0.290) | (1.062) | (1.167) | (0.706) |
| Log income | 0.095 | -0.057 | -0.073 | -0.380 |
| | (0.188) | (0.684) | (0.737) | (0.356) |
| Urban | 0.228 | 0.371 | 0.429 | 0.270 |
| | (0.340) | (1.142) | (1.233) | (0.671) |
| Age | 0.047* | 0.082 | 0.092 | 0.010 |
| | (0.026) | (0.081) | (0.088) | (0.043) |
| $R^2$ | 0.761 | 0.804 | 0.804 | 0.802 |
| Obs. | 579 | 579 | 579 | 579 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. The omitted category of political coalition is center.

Table SF4: Effects of 3G Coverage on Facebook Activity (Two lags)

| | (1) Page | (2) Likes | (3) Total | (4) Shares |
|---|---|---|---|---|
| 3G Share | 0.501** | 0.507 | 0.615 | -0.103 |
| | (0.201) | (0.667) | (0.729) | (0.432) |
| 3G Share (t-1) | 0.080 | 0.905 | 0.976 | 0.753* |
| | (0.144) | (0.623) | (0.682) | (0.384) |
| 3G Share (t-2) | 0.162 | 1.443* | 1.515 | 0.927 |
| | (0.203) | (0.847) | (0.936) | (0.671) |
| Vote Share | -0.007 | -1.266 | -1.458 | -1.392 |
| | (0.300) | (1.136) | (1.286) | (1.036) |
| Right | -0.188 | -0.106 | -0.203 | 0.018 |
| | (0.152) | (0.475) | (0.534) | (0.243) |
| Ind. | -0.158** | -0.293 | -0.402* | -0.214* |
| | (0.075) | (0.191) | (0.220) | (0.114) |
| Left | -0.635*** | -0.640** | -0.849** | -0.304 |
| | (0.093) | (0.288) | (0.328) | (0.191) |
| Log pop | -0.039 | -0.157 | -0.118 | -0.048 |
| | (0.125) | (0.396) | (0.469) | (0.323) |
| Log income | 0.002 | -0.229 | -0.242 | -0.085 |
| | (0.126) | (0.556) | (0.614) | (0.362) |
| Urban | 0.320 | 1.303 | 1.368 | 0.510 |
| | (0.296) | (1.088) | (1.218) | (0.763) |
| Age | 0.045*** | 0.066 | 0.093 | 0.038 |
| | (0.016) | (0.058) | (0.061) | (0.032) |
| $R^2$ | 0.801 | 0.807 | 0.808 | 0.809 |
| Obs. | 462 | 462 | 462 | 462 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. The omitted category of political coalition is center.

Table SF5: Effects of 4G Coverage on Facebook Activity

| | (1) Page | (2) Likes | (3) Total | (4) Shares |
|---|---|---|---|---|
| Share 4G | -0.312 | -1.337 | -1.330 | -0.291 |
| | (0.258) | (0.946) | (1.053) | (0.825) |
| Share 3G | 0.559*** | 1.240* | 1.417* | 0.581 |
| | (0.190) | (0.685) | (0.742) | (0.425) |
| Log pop | -0.027 | 0.063 | 0.107 | 0.088 |
| | (0.126) | (0.435) | (0.488) | (0.315) |
| Log income | 0.029 | -0.174 | -0.204 | -0.158 |
| | (0.105) | (0.444) | (0.494) | (0.324) |
| Urban | 0.250 | 1.115 | 1.226 | 0.632 |
| | (0.311) | (0.971) | (1.092) | (0.587) |
| Age | 0.041** | 0.106* | 0.133** | 0.067** |
| | (0.017) | (0.056) | (0.060) | (0.032) |
| $R^2$ | 0.797 | 0.816 | 0.815 | 0.822 |
| Obs. | 469 | 469 | 469 | 469 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district-year level. The sample size for these regressions correspond to politician*years in the 2013-2017 congressional session. All models include politician*district and region*year fixed effects. Models are adjusted for 3G coverage, log of population, log of income, urban status and average age. Given that I am including one congressional session, I could not include vote share and political coalition due to collinearity.

Table SF6: Effects of 3G on Extremeness

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Share 3G | .098 | 0.070 | 0.108 | 0.085 |
| | (0.076) | (0.066) | (0.078) | (0.064) |
| Share 3G (t-1) | | | -0.000 | 0.030 |
| | | | (0.057) | (0.056) |
| Vote Share | | -0.964*** | | -0.917*** |
| | | (0.165) | | (0.170) |
| Right | | 0.088 | | 0.109* |
| | | (0.070) | | (0.065) |
| Ind. | | 0.084 | | 0.122** |
| | | (0.051) | | (0.051) |
| Left | | 0.054 | | 0.068 |
| | | (0.060) | | (0.057) |
| Log pop | | 0.036 | | 0.026 |
| | | (0.033) | | (0.035) |
| Log income | | -0.095** | | -0.092** |
| | | (0.042) | | (0.038) |
| Urban | | 0.091 | | 0.102 |
| | | (0.068) | | (0.066) |
| Age | | 0.011** | | 0.015*** |
| | | (0.005) | | (0.005) |
| $R^2$ | 0.727 | 0.774 | 0.758 | 0.799 |
| Obs. | 826 | 814 | 664 | 656 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. The outcome for all regressions is the level of extremeness in congress. All models include politician*district and region*year fixed effects. The omitted category of political coalition is center.

Table SF7: Effects of Facebook Activity on Extremeness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Page (t-1) | 0.043 | 0.045* | | | | | | |
| | (0.026) | (0.024) | | | | | | |
| Likes (t-1) | | | 0.029*** | 0.026*** | | | | |
| | | | (0.009) | (0.008) | | | | |
| Total (t-1) | | | | | 0.027*** | 0.024*** | | |
| | | | | | (0.008) | (0.007) | | |
| Shares (t-1) | | | | | | | 0.039*** | 0.032*** |
| | | | | | | | (0.009) | (0.008) |
| Vote Share | | -0.928*** | | -0.910*** | | -0.907*** | | -0.888*** |
| | | (0.188) | | (0.186) | | (0.184) | | (0.180) |
| Right | | 0.086 | | 0.083 | | 0.082 | | 0.077 |
| | | (0.075) | | (0.074) | | (0.074) | | (0.071) |
| Ind. | | 0.090 | | 0.092 | | 0.093 | | 0.090* |
| | | (0.057) | | (0.057) | | (0.058) | | (0.054) |
| Left | | 0.041 | | 0.028 | | 0.028 | | 0.044 |
| | | (0.064) | | (0.065) | | (0.065) | | (0.062) |
| Log pop | | 0.033 | | 0.035 | | 0.035 | | 0.038 |
| | | (0.035) | | (0.033) | | (0.033) | | (0.036) |
| Log income | | -0.108** | | -0.099** | | -0.099** | | -0.102** |
| | | (0.045) | | (0.044) | | (0.044) | | (0.045) |
| Urban | | 0.118 | | 0.117 | | 0.119 | | 0.117 |
| | | (0.077) | | (0.078) | | (0.077) | | (0.078) |
| Age | | 0.011** | | 0.011** | | 0.011** | | 0.012** |
| | | (0.005) | | (0.005) | | (0.005) | | (0.005) |
| $R^2$ | 0.820 | 0.849 | 0.825 | 0.852 | 0.825 | 0.853 | 0.825 | 0.851 |
| Obs. | 1145 | 1137 | 1145 | 1137 | 1145 | 1137 | 1145 | 1137 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. The outcome for all regressions is the level of extremeness in congress. All models include politician*district and region*year fixed effects. The omitted category of political coalition is center.

Table SF8: Effects of Facebook Activity on Extremeness (leads and lags)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Page (t+2) | -0.002 | | | |
| | (0.028) | | | |
| Page (t+1) | -0.020 | | | |
| | (0.024) | | | |
| Page | 0.018 | | | |
| | (0.018) | | | |
| Page (t-1) | 0.039 | | | |
| | (0.024) | | | |
| Likes (t+2) | | 0.009 | | |
| | | (0.008) | | |
| Likes (t+1) | | -0.006 | | |
| | | (0.006) | | |
| Likes | | 0.009 | | |
| | | (0.006) | | |
| Likes (t-1) | | 0.027*** | | |
| | | (0.008) | | |
| Total (t+2) | | | 0.005 | |
| | | | (0.007) | |
| Total (t+1) | | | -0.004 | |
| | | | (0.006) | |
| Total | | | 0.008 | |
| | | | (0.005) | |
| Total (t-1) | | | 0.024*** | |
| | | | (0.007) | |
| Shares (t+2) | | | | 0.005 |
| | | | | (0.011) |
| Shares (t+1) | | | | 0.003 |
| | | | | (0.009) |
| Shares | | | | 0.009 |
| | | | | (0.008) |
| Shares (t-1) | | | | 0.033*** |
| | | | | (0.010) |
| Vote Share | -0.947*** | -0.937*** | -0.931*** | -0.897*** |
| | (0.183) | (0.183) | (0.181) | (0.177) |
| Right | 0.077 | 0.095 | 0.092 | 0.087 |
| | (0.086) | (0.088) | (0.089) | (0.083) |
| Ind. | 0.064 | 0.079 | 0.079 | 0.081 |
| | (0.072) | (0.078) | (0.079) | (0.071) |
| Left | -0.006 | -0.015 | -0.012 | 0.005 |
| | (0.085) | (0.087) | (0.088) | (0.079) |
| Log pop | -0.068 | -0.051 | -0.056 | -0.055 |
| | (0.044) | (0.044) | (0.044) | (0.046) |
| Log income | -0.213*** | -0.184*** | -0.189*** | -0.194** |
| | (0.070) | (0.068) | (0.068) | (0.073) |
| Urban | 0.199* | 0.201* | 0.204* | 0.207* |
| | (0.106) | (0.104) | (0.105) | (0.105) |
| Age | 0.007 | 0.008 | 0.008 | 0.009* |
| | (0.006) | (0.005) | (0.005) | (0.005) |
| $R^2$ | 0.830 | 0.836 | 0.836 | 0.833 |
| Obs. | 639 | 639 | 639 | 639 |



*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. The outcome for all regressions is the level of extremeness in congress. All models include politician*district and region*year fixed effects. The omitted category of political coalition is center.

Table SF9: Instrumental Variable Estimates. Outcome: Extremeness

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Page (t-1) | 0.028 | 0.026 | | | | | | |
| | (0.112) | (0.097) | | | | | | |
| Likes (t-1) | | | 0.021 | 0.054 | | | | |
| | | | (0.053) | (0.037) | | | | |
| Total (t-1) | | | | | 0.127*** | 0.048 | | |
| | | | | | (0.046) | (0.032) | | |
| Shares (t-1) | | | | | | | 0.288*** | 0.132** |
| | | | | | | | (0.100) | (0.056) |
| Vote Share | | -0.907*** | | -0.876*** | | -0.872*** | | -0.736*** |
| | | (0.184) | | (0.191) | | (0.188) | | (0.200) |
| Right | | 0.104 | | 0.107 | | 0.106 | | 0.083 |
| | | (0.067) | | (0.075) | | (0.076) | | (0.070) |
| Ind. | | 0.115** | | 0.132** | | 0.132* | | 0.147** |
| | | (0.053) | | (0.066) | | (0.066) | | (0.066) |
| Left | | 0.048 | | -0.001 | | 0.001 | | 0.023 |
| | | (0.068) | | (0.077) | | (0.077) | | (0.072) |
| Log pop | | 0.029 | | 0.030 | | 0.029 | | 0.040 |
| | | (0.035) | | (0.030) | | (0.031) | | (0.037) |
| Log income | | -0.096** | | -0.080** | | -0.082** | | -0.071* |
| | | (0.039) | | (0.034) | | (0.034) | | (0.036) |
| Urban | | 0.116 | | 0.112 | | 0.116 | | 0.110 |
| | | (0.072) | | (0.077) | | (0.077) | | (0.094) |
| Age | | 0.014*** | | 0.015*** | | 0.015*** | | 0.020*** |
| | | (0.005) | | (0.005) | | (0.005) | | (0.006) |
| $R^2$ | 0.00836 | 0.178 | 0.0310 | 0.160 | -0.552 | 0.165 | -1.237 | -0.00322 |
| Obs. | 660 | 660 | 669 | 660 | 660 | 660 | 660 | 660 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the district level. The sample size includes politician*years between 2011 and 2018, the period covered by the 3G data. All models include politician*district and region*year fixed effects. The adjusted models control for log of population, log of income, urban status, average age, vote share, and political coalition. The omitted category of political coalition is center.

Table SF10: Effects of 3G on Democracy Best Government (Before Facebook Page).

| | (1) Support Dem. | (2) Support Dem. | (3) Conf. Elections | (4) Conf. Elections |
|---|---|---|---|---|
| Share 3G | -0.278 | -0.341 | -0.324 | -0.302 |
| | (0.238) | (0.299) | (0.243) | (0.236) |
| Urban | | -0.200 | | 0.023* |
| | | (0.126) | | (0.013) |
| Female | | -0.041 | | -0.013 |
| | | (0.027) | | (0.022) |
| Income (ordinal) | | 0.005 | | 0.004 |
| | | (0.004) | | (0.004) |
| Education (years) | | -0.004 | | -0.005 |
| | | (0.004) | | (0.004) |
| Adjusted | No | Yes | No | Yes |
| $R^2$ | 0.189 | 0.205 | 0.148 | 0.153 |
| Obs. | 1737 | 1450 | 1840 | 1504 |

Effects of 3G on Democracy Best Government (After Facebook Page).

| | (1) Support Dem. | (2) Support Dem. | (3) Conf. Elections | (4) Conf. Elections |
|---|---|---|---|---|
| Share 3G | -0.310* | -0.322* | -0.161 | -0.116 |
| | (0.168) | (0.186) | (0.115) | (0.123) |
| Urban | | -0.025 | | -0.064 |
| | | (0.046) | | (0.058) |
| Female | | -0.021 | | -0.049*** |
| | | (0.018) | | (0.019) |
| Income (ordinal) | | 0.004 | | 0.003 |
| | | (0.003) | | (0.002) |
| Education (years) | | 0.007*** | | -0.001 |
| | | (0.002) | | (0.003) |
| Adjusted | No | Yes | No | Yes |
| $R^2$ | 0.0766 | 0.0882 | 0.0562 | 0.0601 |
| Obs. | 3779 | 3188 | 3870 | 3258 |

*p<.1; **p<.05; ***p<.01. Standard errors are clustered at the municipality level. All models include municipality and year fixed effects. Adjusted models control for income, education, urban status, and gender. The omitted category of political coalition is center.

Guriev, Sergei, Nikita Melnikov, and Ekaterina Zhuravskaya. 2021. "3G Internet and Confidence in Government*". *The Quarterly Journal of Economics* 136, no. 4 (): 2533–2613. ISSN: 0033-5533, visited on 10/18/2021. doi:10.1093/qje/qjaa040. https:2//doi.org/10.1093/qje/qjaa040.