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Politicians' willingness to agree: evidence from the interactions in twitter of Chilean deputies

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ABSTRACT
We contrast the number of "likes" that a given politician gives to another one on Twitter and the number of bills voted in favor by the same pair of politicians to empirically study how signals of agreement in Twitter translate into cross-cutting voting during a highly polarized period of time. As our main contribution, we document empirical evidence that "likes" between opponents are positively related to the number of bills voted by the same pair of politicians in Congress, even when we control by politicians' time-invariant characteristics, coalition affiliation, directed and undirected dyads and following links in Twitter.

KEYWORDS
Disagreement; polarization; twitter

Introduction

Since Poole and Rosenthal (1985), researchers have tried to infer politicians' ideology using voting data. Similar analysis has also been conducted using campaign contributions (Bonica, 2013), surveys and texts (Laver, 2014). Bølstad and Dinas (2017), suggest that applications of spatial voting theory can successfully identify clusters of political actors associated with the same ideology (e.g. left and right-wing coalitions).[1] However, this methodology is mostly agnostic considering the many endogenous factors that determine the positions of political actors in a given network, being effective on localizing them but not on offering explanations on how and why they reached that position.[2] In this paper, we contribute to shorten this gap by studying how signals of affection in Twitter correlates to cross-cutting votes in Congress.,[3] [4]

We follow Barberá (2015), who complements the analysis of politicians' behavior using interactions in Twitter (e.g. "retweets" and "following" links) of U.S. political actors.[5] Specifically, we augment the analysis of politicians' behavior by combining Twitter interactions with voting data from Congress. We analyze Twitter "likes," a strong signal of appreciation from one legislator to another, to measure signals of agreement into the public political debate among politicians in Chile.[6] The above empirical setting is used to test the main hypotheses of this paper as follows: considering the dynamics of communication in Twitter being of noisy type, then it should be translated into a non-agreement scheme for the voting process, after being controlled by time-invariant features such as coalition affiliation, "following links" in Twitter and time fixed effects.[7]

The main empirical result found in this paper, which includes different types of control variables, is that on the average, politicians reaching consensus on Twitter will agree on a lesser degree in Congress. This empirically puzzling result is explained by a differential effect based on coalition affiliation. That is, signals of agreement in Twitter are positively (marginally negatively) correlated in the case of coalition opponents (mates) in Congress. The above result stands out among alternate explanations, capturing a multitude of reasons on why political opponents could reach agreement both in Congress as well as Twitter. These results survive controls for alternative explanations that capture other reasons that explain why political opponents can be agreeing both in Congress and Twitter. Different clustering criteria, as in Harmon, Fisman, and Kamenica (2019), help to deal with the risk of underestimating the standard errors of our estimates, as well as the inclusion of weights regarding selection bias, as proposed by Solon, Haider, and Wooldridge (2015).

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We rationalize our results through a public choice model. In our model, politicians use Twitter "likes" as signals for manipulating voters' beliefs. In this work, we follow a novel approach by introducing a nonstandard-intrinsic factor called authenticity, motivated by Trilling (2009). In simple terms, this factor accounts for those actions taken by an individual such that they remain consistent with their own beliefs. In the case of politicians, they will weigh being consistent with their own ideology. The model is standard in the sense that politicians decide based on electoral incentives (popularity). Our theory suggests that "likes" among political opponents are costly. In our model, a politician would only "like" an opponent's tweet if there is ideological agreement, or if expected political gains compensate the loss of authenticity. On the other hand, coalition mate "likes" are less informative regarding agreement in Congress since popularity plays a bigger role in determining their behavior in the signaling market. The practical implications of our empirical results are related to the possibility of using Twitter as a source of information to analyze how political opponents reach agreement.

Chile is a relevant setting to test our hypothesis. Our interest is related to the different political cleavages that have shaped the political landscape since return to democracy in 1990 (Bonilla, Carlin, Love, & Méndez, 2011), as well as the evidence of "centrifugal forces" generated by the electoral system first documented in Dow (1998). After the return of democracy, Chile set up for a fast-paced economic development, sustained on free market-oriented policies and a stable political system, that transformed Chile as one of the best performing countries in the region (Barro, 1999). However, in October 2019, after almost three decades of sustained growth, the country's social stability crumbled after huge protests and popular demonstrations against economic inequality. The political parties reacted by proposing a referendum to reform Pinochet's Constitution. In October 2020, a referendum took place, with an overwhelming majority approving the rewriting of the Constitution through a democratically elected Constitutional Assembly. Consequently, we argue that the current political situation in Chile offers a unique setting to analyze how politicians can reach agreement in highly polarized political environments.

In this paper, we intend to make a twofold contribution to the existing literature. First, we contribute to the empirical spatial voting literature pioneered by Poole and Rosenthal (1985), which focuses on identifying coalitions and other political associations using data on politicians voting behavior, campaign contributions (Bonica, 2013), or surveys and text (Laver, 2014).[8] We offer a link between Machine Learning research that use political science data to measure political polarization using the modularity of the political network, an idea firstly proposed by Zhang et al. (2008) and extended in Waugh, Pei, Fowler, Mucha, and Porter (2009). Secondly, on the subject of political disagreement, we introduce a working scheme to the existing multidisciplinary literature, which intends to understand the mechanism on how rational thinking mechanisms, as in Habermas (1998) or Aumann (1976), relate with different social science theories. Our empirical results suggest that Twitter "likes" are consistent with theory only when signals of agreement are observed among political opponents. A theoretical approach is given, which could explain how politicians' authenticity imposes a cost on the agreement process in Twitter among representatives with different political identities.

The paper is organized as follows: In Section 2, we describe Chile's institutional framework. In Section 3 we review relevant related literature in spatial voting theory, political disagreement and polarization, highlighting how they connect with the present study. Section 4 proposes a theory to interpret our empirical results. Section 5 provides a description of our three data sets: the CEP survey, interactions of politicians in Twitter and the bills voted in the Chilean Chamber of Deputies. Section 6 details our empirical approach to test our proposed hypothesis. In Section 7 we present our empirical results. Finally, in Section 8 we provide our main conclusions with some open-ended discussion questions for future research.

Institutional framework

Chile returned to democracy in 1989 after the end of Pinochet's dictatorship. This was possible due to the referendum held in 1988, known as The Victory of the No, where Chileans opted-out of Pinochet's rule. One year later, in 1989, Patricio Aylwin

became the first democratic-elected president since 1970. However, the Dictatorship's Constitution remained in place.[9] It established a division of Congress into two Chambers: The Chamber of Deputies with 120 members, and the Senate with 38 members. The electoral system that ruled the allocation of seats in both chambers was a variant of the well-studied D'Hondt electoral system, locally known as "Binominal." As has been analyzed by Dow (1998), the Chilean variant forced the establishment of two coalitions formed by multiple parties. This incentive is set by mandating that each coalition presents two candidates in each district. The "Binominal" system awarded the first seat based on the largest number of votes by coalition. However, if the combined number of votes is more than two-thirds of the total votes in that district, the candidates of the same coalition win both seats. Else, one seat goes to each coalition. Authors have suggested that proponents of the system believed that it maintained political stability, while causing at the same time a process known as *malapportionment* (Riquelme, González-Cantergiani, & Godoy, 2018). Moreover, Dow (1998) suggests that it favored extremists and punished moderates.

After 23 years, in 2013, the new-formed left-wing coalition La Nueva Mayoría set one of their main goals to reform the electoral system to increase the representation of new groups that had been excluded from parliamentary representation.[10] In 2017, the Chilean electoral system was reformed into a traditional D'Hondt system, which increased the Chamber of Deputies from 120 to 155 seats, and the Senate from 38 to 50 seats. This reform coincided with the downfall of the center-left coalition, and the increasing representation of the radical left and right-wing groups (Bunker, 2020). Moreover, Fábrega, González, and Lindh (2018) suggest that this electoral reform is related to a latent political polarization that started in the 2000′s.[11] In October 2019, a social and political crisis unfolded in Chile. The triggering factor was the increase in the fare of Santiago's public transportation system, which came into effect on Sunday, October 6, 2019. After the increase, thousands of high-school students organized themselves to carry out massive evasions in Santiago's Subway System. Later that month, social and political unrest grew stronger until several Subway stations were burned, forcing the right-wing government to declare a State of Emergency. After several weeks of massive marches and manifestations denouncing economic and social inequality, the political class in its majority came together to offer a way out later-called the "Agreement for the peace and a New Constitution" which promised a referendum on whether to change the 1980′s Constitution and who should write the new one.[12] Moreover, during 2020 Chile has been affected by the COVID crisis, which in the context of the 2019 social outbreak, has been a new source of disagreement for Chilean politics (Oyarzún-Serrano, 2020). Therefore, recent events in Chile's political, institutional, and economic history accounts for a highly polarized context.

Related literature

We intend to make a two-fold contribution to the existing literature on the subject. First, by complementing the empirical studies on spatial voting that focus on recovering estimates of politicians' preferences, away from their observed voting behavior, a methodological approach pioneered by Poole and Rosenthal (1985). In more recent times, the same approach has included other types of data sets, such as campaign contributions (Bonica, 2013), or surveys and texts (Laver, 2014). As Bølstad and Dinas (2017) suggest, applying this methodological approach, several studies can successfully claim that they are able to identify coalitions and other political associations. As stated before, these approaches tend to be agnostic regarding those factors which can explain why two politicians are voting in favor of the same law, other than the estimated ideological closeness. In this paper, following Barberá (2015) we sort of generalize the analysis of voting data by adding interactions in Twitter. As opposed to Barberá (2015), who analyzes 'retweets', we focus on 'likes' among deputies. We posit that 'likes' are a more direct signal of appreciation than other signals like, for example, 'retweets' which have been used to understand social networks in other contexts (Wachs, Hannák, Vörös, & Daróczy, 2017). Specifically, we connect these ideas with the literature on Machine Learning that analyzes voting data to study polarization using modularity, a metric taken from network theory.[13] .

Our second contribution is to the studies of political disagreement. Hinich and Munger (1996) propose that ideologies are a way to resolve political disagreement with respect to three questions: what is good, who gets what and who rules. In this interpretation, ideologies work as theorizations of politicians' own position in the political arena (Martin, 2015).[14] In practice, political disagreement would take the form of arguments.[15] In the "ideal speech situation" posed by Habermas (1979), if all parties seek the truth and they do not behave strategically, this would lead to the "best argument" to win, as has been argued by Habermas (1998). Moreover, in theory, it is well known since Aumann (1976) that, if it is common knowledge that both parties are Bayesian rational, then they cannot agree to disagree on matters of fact. These theoretical results enter in contradiction with the empirical evidence that suggest that disagreement is a very persistent process, a finding which has also been associated with behavioral theories of homophily (Halberstam & Knight, 2016) or identity (Taylor & Bosworth, 2020). At the same time, other authors argue that the internet have exacerbated the emergence of echo chambers (Sunstein, 2008). We contribute to this literature by adding new data from Twitter, that allows us to identify instances of agreement between politicians, and matching it with bills voted in favor in Congress. Through a public choice model, we argue that Twitter data can be used to shed light on the willingness to agree among political opponents.

Theory

In this section, we outline a public choice model used to interpret the cross-section of "likes" in Twitter among Congress members. The model considers a finite number of politicians which compete into a voting market. We assume that the voting market is populated by politicians that have different ideological types. An ideology type i is well described by draws from a normal distribution with parameters μ_i and σ_i.[16] On the other hand, voters form beliefs about politicians' ideological positions. Voters can be simply characterized by a discrete distribution in a one-dimensional political axis (right-to-left wing). Society is fragmented into K political groups with ideology (i_k) and a population weight (p_k).[17] Specifically, we highlight that in our model a normally distributed electoral population is related to less polarization among elected politicians.

The dynamics of political competition into the model occurs within coalitions, or ideology groups. This assumption is related to the D'Hondt proportional representation rule which governs the Chilean Chamber of Deputies, and which seeks to elect Congress members proportionally so as to have a better electoral population.[18] Into this model, N politicians sort into n coalitions. Then, within the coalition, politicians gain electoral power based on the minimum distance among all competitors within the group. The ideological distance between a politician i and a group of voters k is calculated as follows:

$$d_{i,k} = (\mu_i - i_k)\frac{1}{w_k} \tag{1}$$

where a positive (negative) value of $d_{i,k}$ measures how much to the left (right) is a politician i from group k located, and $\frac{1}{w_k}$ is a factor which penalizes the focus on smaller groups of voters.

Politicians, within a coalition, compete based on a distance $d_{i,k}$. Political power within the coalition is related to votes, which are endogenously determined by the distance between politician i and political group k:

$$1_{i,k} = \begin{cases} 1 & \text{if } d_{i,k} = min\{d_{i,1}, \ldots, d_{i,K}\}, \\ 0 & \text{if otherwise} \end{cases}$$

By assumption, within the group, political power depends on the number of votes (weighted by population) that a politician obtains:

$$v_i = \sum_{k=1}^{K} 1_{i,k} w_k \tag{2}$$

The ideology of the political front-runner, within the coalition, is based on the highest number of votes within the coalition:

$$\mu_k^f = \begin{cases} \mu_i & \text{if } v_{i,k} = max\{v_1, \ldots, v_{N_k}\}, \\ 0 & \text{if otherwise} \end{cases}$$

where N_k is the number of politicians that compete in coalition k.

In our model, politicians use Twitter to manipulate voters' posterior beliefs. Manipulation occurs through the effect in which a signal is sent by a politician i to voters at the instant they give a "like" to a message sent by a politician j ($\delta_{i,j}$). The above under the assumption that signals come from a normally distributed likelihood function with known variance equal to σ_i. Posteriors beliefs from the voters perspective can be determined as a simple weighted average:

$$\mu_i^* = \frac{\mu_i}{1+\omega} + \frac{\omega}{1+\omega}\delta_{i,j} \tag{3}$$

where ω captures how much voters weight the signal ($\delta_{i,j}$) versus their prior view (μ_j) on politician j.

We define the endogenous variable $l_{i,j}$ as a dummy variable which takes the value 1, if and only if, politician i gives a "like" to politician j's message, and zero otherwise. Assuming self-interest preferences, if a politician decides to "like" a message of another politician j if it increases that politician's popularity ($\Delta P(l_{i,j})$). A politician's popularity is measured by distance, or proximity, in a right-left axis as has been empirically suggested by Busch (2016) using data from Europe.

Contrarily, we incorporate an additional factor that influences politicians' behavior, which is motivated by the idea of authenticity developed by Trilling (2009). Because of the above we have included an authenticity parameter (γ) which measures a politician's capacity to reach agreement in public argumentation (Haberrmas, 2006). In other words, politicians apply a factor γ to the inconvenience of giving a "like" to some political message which is far from its own ideology (μ_i). In Section 4.2 we show that this parameter generates ideological consistency. However, at the same time reinforces the propensity to give a like to a message that is ideologically appealing, regardless of the identity of the message sender. In our model, this ideological distance is measured by $\Delta A(l_{i,j})$. The decision of politician i to give a "like" to politician j's message ($\delta_{i,j}$) can be formulated as follows:

$$\max_{l_{i,j}} \quad \Delta P(l_{i,j}) - \gamma \Delta A(l_{i,j}) \tag{4}$$

where $\Delta P(l_{i,j} = 1)$ measures the absolute change of politician i's ideological distance with her front-runner candidate (f), before ($|\mu_i - \mu_k^f|$) and after giving the "like" ($|\mu_i^* - \mu_k^f|$). A positive (negative) value for ΔP measures electoral gains (losses) out of giving a "like" to a message $\delta_{i,j}$. On the other hand, $\Delta A(l_{i,j} = 1)$ measures how far is the message from politician's own ideology ($|\delta_{i,j} - \mu_i|/\sigma_i$).

Model parameters

We solve the model for a set of parameters taken from the CEP opinion survey. In simulations of the model, we use the ideological levels, as well as the proportion of voters documented in Figure 1.[19]

Parameters which describe a politicians' ideology (μ_i and σ_i) are also taken from the same opinion survey. Estimates are obtained by an OLS regression of surveyed subjective evaluation related to a set of 28 politicians on self-reported ideology. Our estimates allow us to have a measure of public opinion on perceived ideology for a set of Chilean politicians. Intuitively, this measure is based on the correlation between subjective opinion and self-reported ideology.[20] The mean and standard error of the coefficients plotted in Figure 2 determine politicians' ideology (μ_i and σ_i).

Model simulation

In this section, we show predictions of our proposed model. It is important to highlight first that our results are based on $\omega = 1$, which is equivalent to assuming that voters equally weight politicians' prior ideology and the observed signal related to the given "like." Secondly, in this model, the political market (e.g. politician and voters' ideology distribution) is well described by the parameters presented in Section 4.1.

In Figure C1 we can see how our model generates a behavior that can explain how politicians at the extremes of the spectrum do not have incentives to move toward the center. Secondly, although not all politicians have incentives to interact with their political opponents, in the first panel of Figure 3 we can see that our model still generates a fair amount of "likes" between political opponents. The aforementioned behavior occurs in the self-interested version. In the following panels of Figure 3, we show how the simulated networks of "likes" change for different levels of authenticity (γ), assuming homogeneous preferences. Visually, we can see

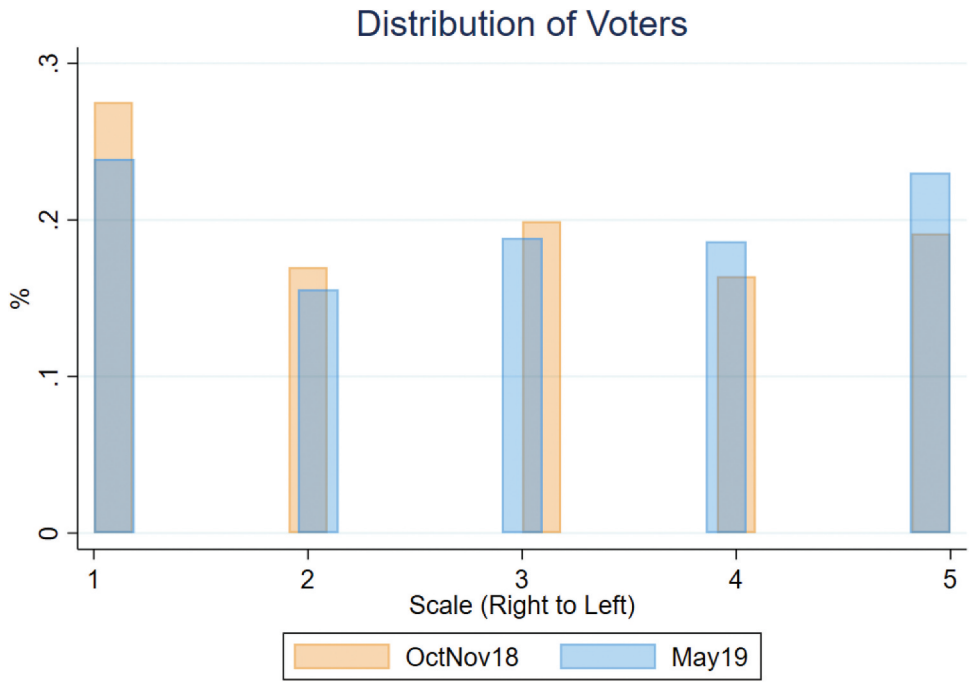

Figure 1. The figure measures the percentage of people in Chile that is associated with each ideology group, a scale from 1 to 5. Null responses are uniformally distributed.

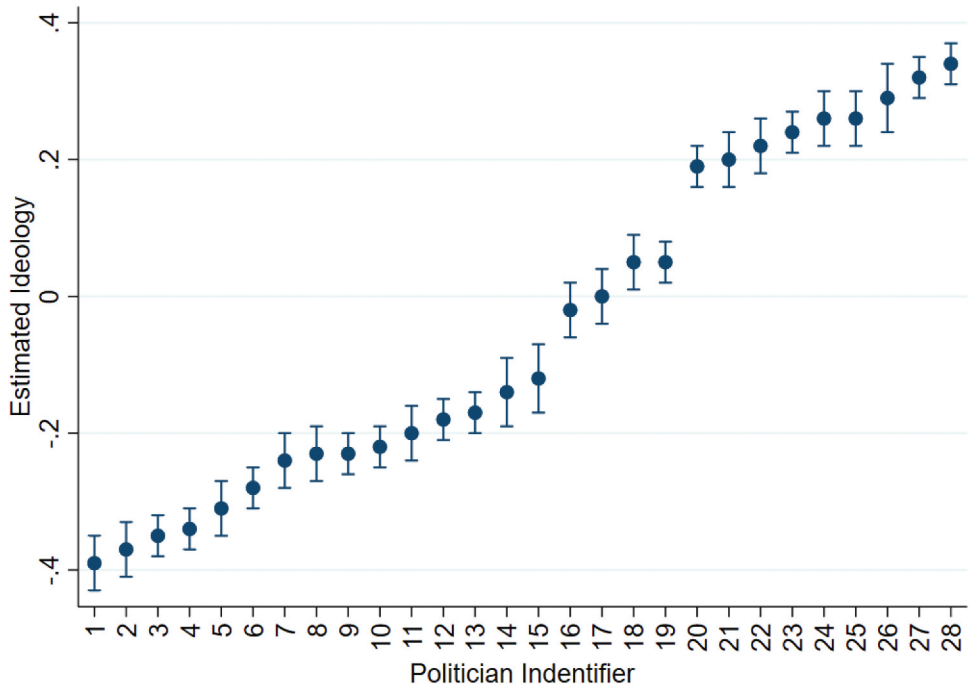

Figure 2. The figure plots the mean and the standard deviation of the ideological distribution of each politician in the model. Politicians are sorted from right to left.

that if all politicians behave more authentically at the same time, the model generates "echo chambers" where only some politicians interact among each other. As proposed in Section 5.2, in

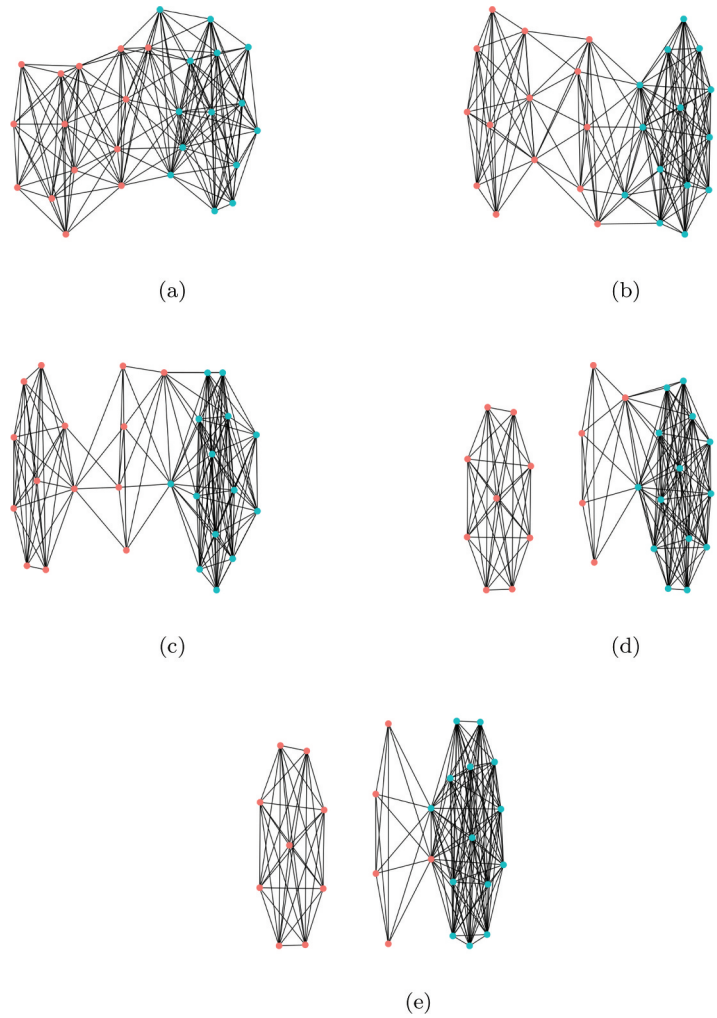

Figure 3. Simulated network analysis by authenticity. This figure plots the estimated network of simulated "likes." Panel (a) shows the case of politicians with no authenticity ($\gamma = 0$); Panel (b) $\gamma = 0.05$; Panel (c) $\gamma = 0.1$; Panel (d) $\gamma = 0.15$; Panel (e) $\gamma = 0.2$.

Figure 4 we confirm that a systematic increase in politicians' authenticity is related to higher polarization, measured by networks' modularity.

Finally, we show a simulation based on heterogeneous levels of politicians' authenticity, which are randomly endowed, independently of politicians' ideology. By assumption, authenticity is normally distributed with mean and standard deviation of 0.1, with a lower bound at zero. The simulated networks of "likes" is analyzed based on the following regression analysis:

$$\text{Likes}_{i,j} = \alpha + \beta \cdot \text{Opponents}_{i,j} + \in_{i,j} \qquad (5)$$

where $\text{Likes}_{i,j}$ measures the number of simulated "likes" between politician i and j; Opponents is a dummy variable that takes the value 1 if politicians i and j are opponents; $\in_{i,j}$ is the residual.

The estimated coefficient (β) of the regression is shown in Table 1. As it can be seen, in our model opponents have a lower propensity to "like" each other's messages. In Figure 5 the relationship between the residual of Equation 5 and the first principal component of politicians' ideology and authenticity. This relationship shows that "likes" between opponents are confined to politicians that have higher levels of

Table 1. Regression of simulated model.

	Coefficients
Opponents	−172.043
	(10.614)
Constant	177.401
	(10.467)
Observations	784
Adjusted R-squared	0.251

[a]Note: Standard errors in parenthesis.

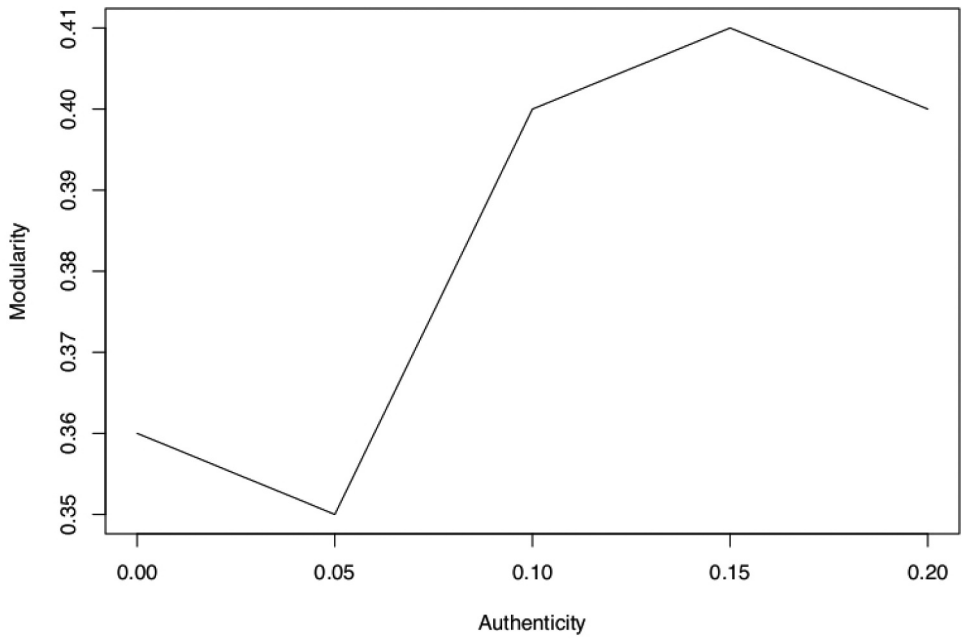

Figure 4. The figure plots the modularity of the simulated networks presented in Figure 3 for different levels of authenticity (γ).

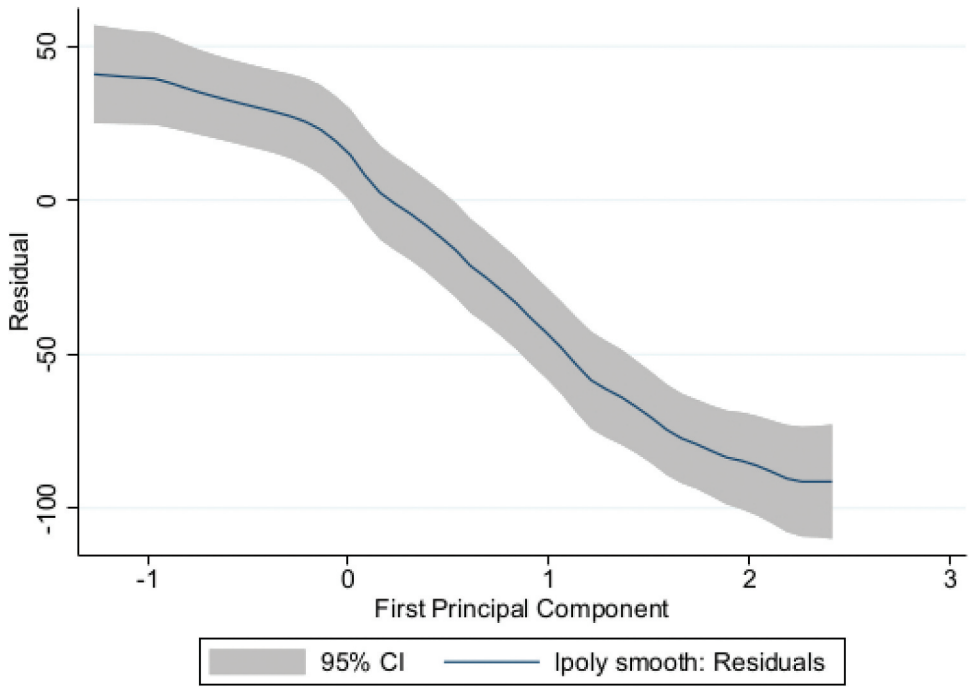

Figure 5. The figure plots the residual of (5) and the first principal component of model input parameters that measure ideology and authenticity.

authenticity and are ideologically closer. In particular, this analysis suggests that, to the extent that we understand politicians' incentives, "likes" between opponents can be informative of politicians authenticity.

Data

Data sources

In this paper, we combine three different public data sources: a public opinion survey conducted by the Centro de Estudios Públicos (CEP), Twitter, and the Chamber of Deputies of Chile.

CEP public political opinion survey

We choose Chile's survey on ideological distribution, a periodical study issued in CEP's public political opinion survey, as it seems to be widely representative of the nation and it has been published periodically since the 1990s We predominantly focus in the May 2019 version, as this issue preceded the Chilean outburst of October 2019.[21 22] The mentioned study surveyed opinions of 1380 citizens belonging to 128 of the most important counties in Chile. In addition to addressing different socio-demographic questions, it also contains a survey of political views of some well-known politicians and their self-reported ideology, which were quantified by defining a discrete 1 to 5 scale.

Figure 1 highlights a deviation from the normal distribution of the estimated non-parametric distribution in which the majority of voters would be bunched around the center. It is worth mentioning that the former figure considers roughly a 55% of people which do not self-identify to any of these categories, a common phenomena seen in Latin American politics (Ruth, 2016).[23] From the same opinion survey, we can recover an estimate of politicians' ideology using people's self-reported ideology variable described above, jointly with their public opinion of well-known politicians. The survey allows to quantify an estimate value of any politician's ideology using as a variable the self-reported ideology, jointly with the public opinion of some well-known political figures.[24] Figure B1 shows a plot of the regression coefficients measuring politician's ideology.[25] Interestingly, our estimates suggest that voters would not see a lack of supply of politicians with different ideologies.[26]

Twitter

Twitter "likes" are obtained using Twitter API. A script was written for collecting the last 500 "likes" for every Chilean deputy that can be tracked in Twitter. Data extraction occurs at different points of time during the 2019–2020 period, which covers October 2019 Chile's political unrest, and the first year of the COVID crisis. For a description of time periods see Table 2. The Twitter database is structured as a panel dataset, where we can track the number of "likes" between deputies during the studied time window. In addition, from the same source we can record if one politician follows another. On average, politicians in our sample send 2.74 messages in Twitter a day. However, the number of messages per day by politician is highly skewed, with the top 10 users "tweeting" more than 8 times a day. In Table 3 we can see that the number of interactions that we are following in Twitter is increasing over time. This is explained by the higher number of deputies that started using Twitter after the Chilean unrest event of October 2019, and also after the COVID crisis started. The average number of "likes" is 0.45 for the whole period. However, this number can vary over time as is observed in Table 3. From the same table, we can see that the probability of observing a deputy giving a "like" to an opponent (Opponents Mean) is less than a tenth of the pooled mean (Opponents All). On the other hand, we also find

Table 2. Analyzed time periods.

Start date	End date	Likes
April 2, 2019	May 28, 2019	May 27, 2019
September 3, 2019	October 20, 2019	October 28, 2019
December 30, 2019	January 30, 2020	February 21, 2020
May 12, 2020	June 10, 2020	June 11, 2020
November 3, 2020	December 2, 2020	December 2, 2020

Table 3. Summary statistics.

	Tweet likes	May-19	Oct-19	Feb-20	Jun-20	Dec-20
All	Mean	0.47	0.48	0.41	0.39	0.49
	Median	0.00	0.00	0.00	0.00	0.00
	Std. Dev.	5.80	5.84	5.12	4.50	5.49
	N	8113	8640	8640	10530	12727
Opponents	Mean	0.02	0.02	0.04	0.03	0.05
	Median	0.00	0.00	0.00	0.00	0.00
	Std. Dev.	0.21	0.21	0.45	0.29	0.48
	N	3980	4252	4252	5180	6339
	Votes in favor	May-19	Oct-19	Feb-20	Jun-20	Dec-20
All	Mean	77.02	91.78	82.52	72.93	82.33
	Median	77.00	92.00	76.00	74.00	75.00
	Std. Dev.	23.72	28.25	35.33	17.19	41.36
	N	8113	8640	8640	10530	12727
Opponents	Mean	68.64	91.96	85.30	73.61	81.29
	Median	68.00	92.00	78.00	75.00	77.00
	Std. Dev.	19.32	27.44	37.59	16.20	32.15
	N	3980	4252	4252	5180	24003

that the unconditional probability that a deputy follows an intra-coalition mate is roughly 47%, which compares higher with the approximately 18% probability that a politician follows an opponent.

Chilean chamber of deputies

Voting records are obtained from the website of the Chilean Chamber of Deputies. Using data scrapping, we collected all voting records from each politician, before Twitter data is collected. A retrieval of data was performed for those interactions in Twitter occurring the same day that Bills were voted. We do this as an intent to study the interactions in Twitter and Congress during the same time window. In Table 3 we can see that, on average, the number of bills voted in favor among all deputies is not very different to the number of bills voted between opponents. This finding is consistent with politicians disagreeing more in Twitter than in Congress.

In addition, using structural topic modeling available through the stm R package developed by Roberts et al. (2014), we automatically analyzed the prevalence of topics mentioned in each period. On this basis, we identified the most prevalent voting topics in each window. In Figure 6 we report the five most frequently cited topics appearing at each of the five mentioned voting periods.

Network construction

In this section, we describe the construction of indirect networks based on the interactions among politicians in Twitter and Congress. Specifically, we define weighted networks $G_i = (V_i, E_i, W_i)$, where V_i is the set of nodes corresponding to "likes" or votes in favor of among politicians, E_i is the set of edges between them, and the edge weights (W_i) corresponds to a Pearson correlation coefficient. By setting as threshold $\theta = 0.1$, correlation matrices can be transformed into correlation networks. In Figures 7 and 8 the set of networks of votes in favor of and "likes" are shown. As it can be observed in the aforementioned table, the density of likes among politicians is lower than the corresponding one in Congress, a fact being consistent with the summary statistics shown in Table 3. In other words, agreement between deputies appear to be more prevalent in Congress than in Twitter. On the other hand, the network figures also suggest that deputies tend to interact more with politicians from the same coalition, which is consistent with the evidence of homophily documented by Halberstam and Knight (2016) by using data from politically-engaged users in Twitter. Nevertheless, our network figures also show that there are deputies which tend to cooperate more with political opponents as has been documented by Andris et al. (2015) using data from the U.S. Congress.

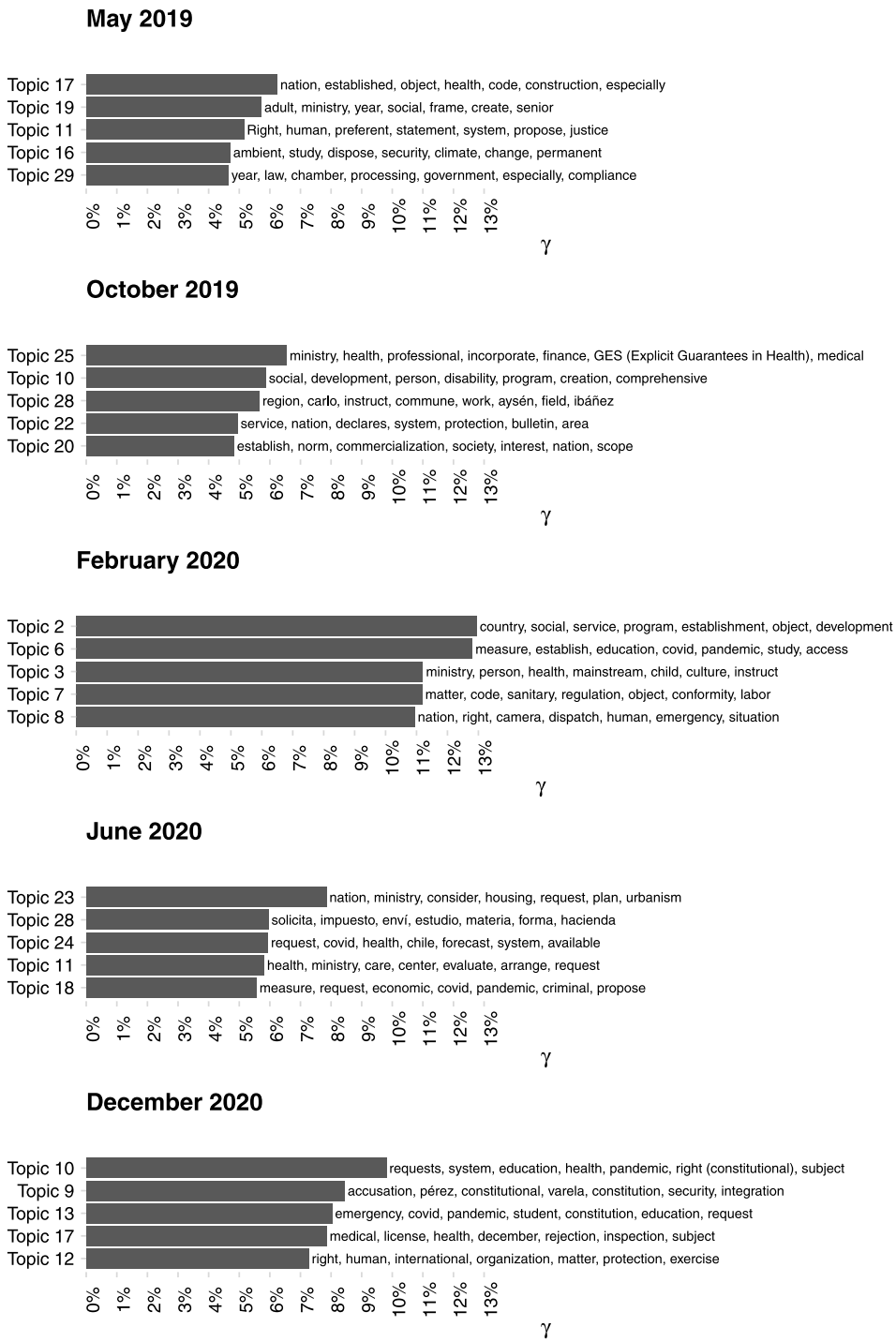

Figure 6. Most prevalent voting topics in each period.

In order to provide a further network characterization, we follow Zhang et al. (2008), which proposes modularity as a measure of political polarization. The modularity of the network is computed by following M. E. J. Newman (2006).[27] In the current application of his method, we need to identify relevant communities in Congress and Twitter in order to quantify the severity of such divisions. Intuitively, modularity measures network segregation into these distinct identified communities. For example, a network with high modularity would be divided into clusters having many internal connections among nodes, and only a few connections to other communities. The relevant

literature shows different ways to identify communities (Ribeiro, Alves, Martins, Lenzi, & Perc, 2018). In the current paper, we use the Louvain algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008), as well as the Edge Betweenness algorithm (M. E. Newman & Girvan, 2004) as a check of robustness.[28] Figure 9 shows the evolution of the modularity of networks constructed with data from Congress and Twitter. Our quantitative analysis corroborates the intuitive aforementioned idea that modularity measures network segregation as provided by Figure 7 and Figure 8. First, the estimated polarization is notably higher in Twitter than in Congress, until the Chilean political unrest events of October 2019. However, our results suggest that this event, as well as the COVID crisis are associated with an important increase in Congress' polarization.[29] [30] Finally, it is important to highlight the fact that our measured levels of polarization in Twitter (≈ 0.4) are consistent with the highest levels of modularity found by Waugh et al. (2009) using roll call votes from the U.S. House during the 1788–2004 period, and Conover et al. (2011) findings obtained from a network of "retweets" related to politically relevant "hashtags" during the congressional midterm election of 2010.

Empirical framework

In Equation 6 we propose a regression model to empirically test whether signals of agreement in Twitter, among Deputies, translate into political agreement in Congress. First, to the extent that Twitter is just noise, as Grant, Moon, and Busby Grant (2010) have suggested, we should first verify if Congress bills voted in favor ($Y_{i,j,t}$) among two politicians i and j at time t should not be related to Twitter "likes" ($\text{Likes}_{i,j,t}$) among the same politicians at the same instant of time. This should be specially true after controlling by their political affiliation ($\text{Opp}_{i,j}$), non-time varying characteristics of the politicians (α_i), systematic changes (α_t), political affiliation and Twitter following links ($\theta_{i,j}$). The above can be translated into the following equation

$$\begin{aligned} Y_{i,j,t} = \alpha_i + \alpha_t + \beta \cdot \text{Likes}_{i,j,t} + \lambda \cdot \text{Likes}^2_{i,j,t} \\ + \beta^O \cdot \text{Likes}_{i,j,t}\text{Opp}_{i,j} + \lambda^O \cdot \text{Likes}^2_{i,j,t} \cdot \text{Opp}_{i,j} \\ + \theta_{i,j} + \in_{i,j,t} \end{aligned} \tag{6}$$

where $Y_{i,j,t}$ is the numbers of "likes" or bills voted in favor of between politician i and j during a time window t, which are used interchangeable

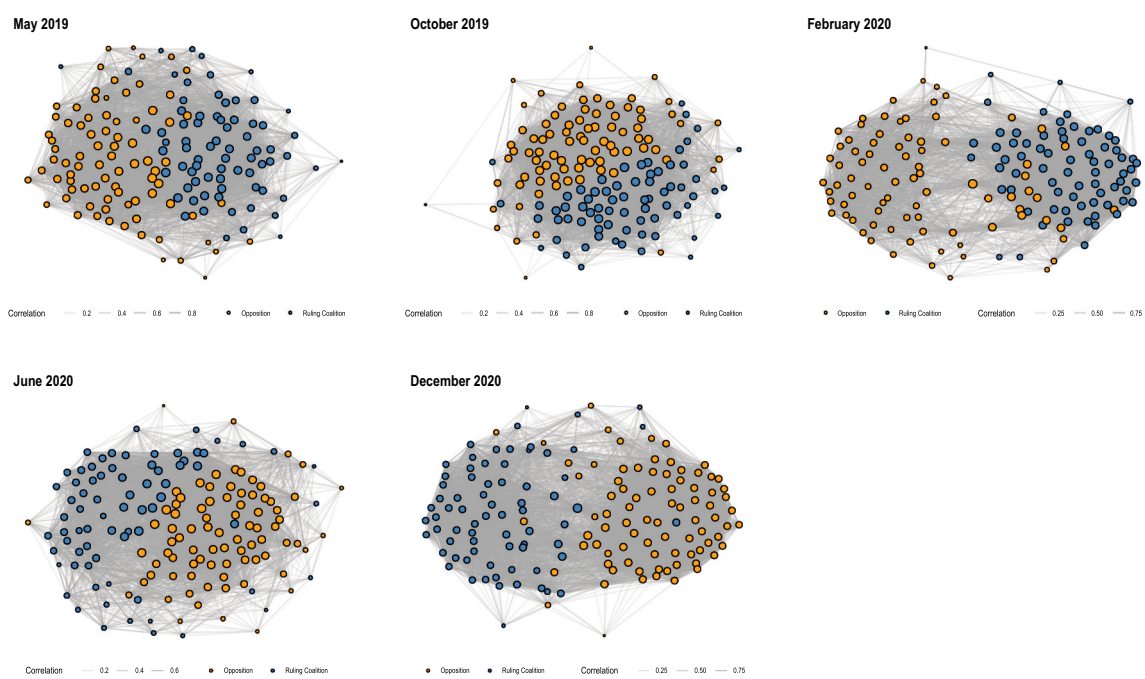

Figure 7. Network analysis of bills voted in favor.

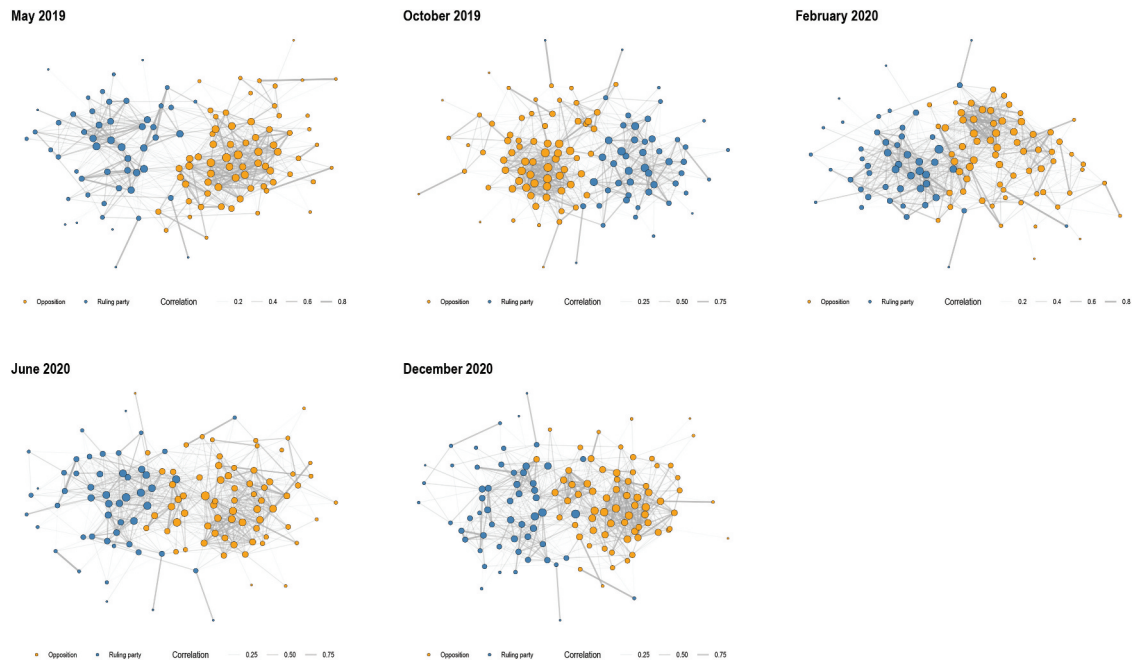

Figure 8. Network analysis of "likes."

according to the different specifications shown in Table 4; $\text{Likes}^2_{i,j,t}$ measures the number of "likes" between politician i and j squared, in order to capture potential nonlinear effects in the relationship of votes and "likes"; $\text{Opp}_{i,j,t}$ is a dummy variable that takes the value 1 if politician i and j are opponents;[31] α_i and α_t are politicians and time fixed effects, respectively; $\theta_{i,j}$ are two dummy variables that are used as non-time-varying control variables, these are indicator functions which identify if politician i follows politician j, and if politician i and j are opponents; $\in_{i,j,t}$ is called residual, a quantity which captures the many different unmeasured factors which could explain why two politicians are voting the same bills in favor of.

The main focus of analysis is related to a study of the parameters β, $\lambda+\beta$ and $\lambda+\beta+\lambda^O$ in Equation 6. First, the coefficient β measures how "likes" correlate to bills voted in Congress. This estimate can shed light on the question about Twitter working as a public sphere. By starting from the hypothesis that considers twitter as a noisy system then this coefficient should be zero. Secondly, $\lambda+\beta$ allows us to study the importance of political identity. Additionally, as Twitter "likes" are a signal of political agreement this number should be positively correlated to the number of bills voted in favor of by two deputies. Finally, to test for a differential effect along political identity we use $\lambda+\beta+\lambda^O$. If "likes" work as costly signals of agreement in the political arena, the positive relationship highlighted before should be concentrated on political opponents.

Finally, our empirical analysis includes politicians' (α_i) and time fixed effects (α_t) as a way of controlling for politicians' time-in-varying propensity to vote bills in favor in Congress and "like" other Deputies comments in Twitter, as well as, to control for systematic changes in the Chilean political environment that affect all politicians during the period of study. Second, given that we are analyzing a dyadic dataset as in Harmon et al. (2019), we cluster our standard errors by undirected politicians' pairs.[32] Third, given that not all Deputies use Twitter, it can be argued that our results can be driven by endogenous sampling. In order to deal with this concern we follow Solon et al. (2015). We estimate our main regression by weighting by the inverse of the OLS prediction of "tweets" per day (since the Twitter account is created) taking the interactions between gender, age, and age-squared as predictors.

Table 4. Politicians interactions in twitter and congress.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Likes	Likes	Likes	Votes	Votes	Votes	Votes	Votes	Votes	Votes
Opponents	−0.812a**		−0.811***	0.275		0.763**		0.486	0.508	1.057***
	(0.088)		(0.122)	(0.336)		(0.359)		(0.359)	(0.359)	(0.385)
Following		0.315***	0.003		1.461***	1.754***	1.488***	1.735***	1.726***	1.581***
		(0.115)	(0.152)		(0.392)	(0.419)	(0.393)	(0.421)	(0.421)	(0.448)
Likes							−0.088	−0.345***	−0.334***	−0.384***
							(0.061)	(0.105)	(0.105)	(0.124)
Likes × Opponent								2.957**	2.914**	3.287**
								(1.213)	(1.212)	(1.362)
$Likes^2$								−0.123	−0.126	−0.130
								(0.140)	(0.140)	(0.133)
$Likes^2$ × Opponent								0.002***	0.002***	0.002***
								(0.000)	(0.000)	(0.001)
Observations	48650	48650	48650	48650	48650	48650	48650	48650	48650	48650
Adjusted R-squared	0.011	0.005	0.011	0.091	0.092	0.092	0.092	0.092	0.060	0.097
Fixed Effects				T & P					P	T & P
Cluster Std. Error					Undirected Pair					
Weights					No					Yes

$p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$; Politician fixed effects (P) and Time Fixed Effects (T); All standard errors are clustered by undirected politicians' pairs; column 10 is a weighted least square regression.

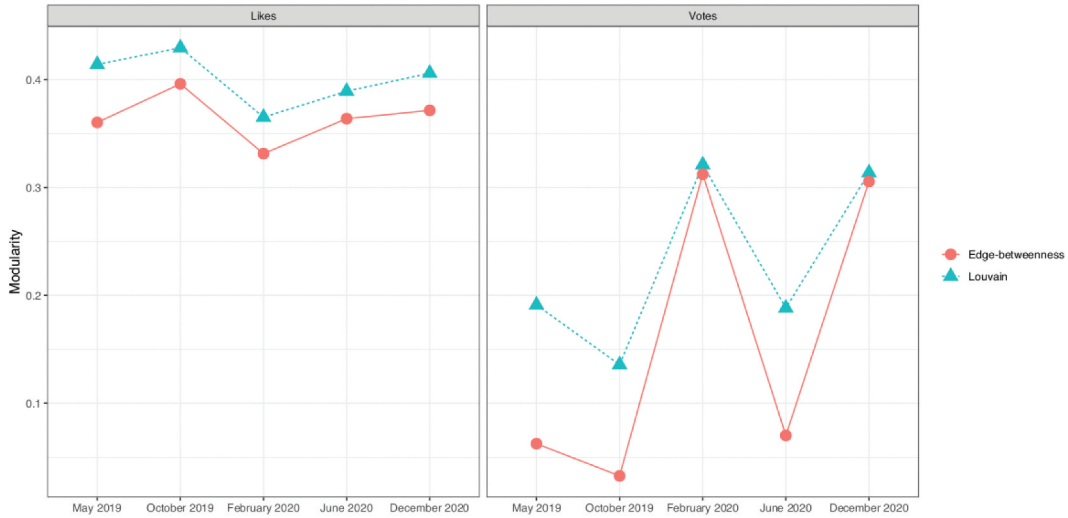

Figure 9. Evolution of the modularity measurement. We considered the groups obtained via community detection method.

Results

This section shows results of a testing implemented in order to verify the deputies' voting behavior and their proclivity to like Twitter messages posted by other politicians.

In columns (1) to (3) in Table 4 we show estimates of a coefficient related to Equation 6 using as a dependent variable the number of "likes." Our findings suggest that deputies have a lower propensity to "like" their opponents' messages, a fact consistent with our theoretical model as well as the empirical evidence documented by Halberstam and Knight (2016). At the same time, our results also suggest that following links cannot explain "likes" when we control for political affiliation, which is consistent with the fact that politicians do want to be attentive about opponents' "tweets."

Columns (4) to (10) of Table 4 use the number of bills voted in favor of as the dependent variable. Interestingly, we find no relationship between bills voted in favor of and coalition membership. This result is consistent with low levels of coalition unity during the studied period. Likewise, a positive relationship between following links and bills voted in favor survives across columns (5) to (10), which suggests that establishing a connection in Twitter can be a signal of political agreement. A surprising result is that during the aforementioned period the number of "likes" in Twitter is negatively related to the number of bills voted in favor of. This finding suggests that a deputy could "like" the "tweet" of a coalition mate as a signal of group loyalty (Brennan & Hamlin, 1998), even when she opportunistically deviates from her coalition in Congress. Finally, columns (8) and (10) document the main finding of this paper. A "like" to an opponent is positive and significantly correlated with future cross-cutting coalition in Congress. The differential effect between intra- and inter-coalition suggests that "likes" between political opponents work as costly signals of ideological agreement. Column (9) shows results which does not include time-fixed effects, in order to highlight the fact that our current results are not affected by time-varying changes that systematically affect all politicians (e.g. systematic polarization). Column (10) shows that our result survives the use of weights that deal with selection bias from more active politicians in Twitter.

Conclusion

This paper tests the hypothesis that Twitter provides relevant information about politicians' legislative decisions. As opposed to some other papers which have used politicians' Twitter data, we focus on the number of "likes" as an observable measurement of agreement between Congress members. Our empirical test intends to isolate the relationship between agreement in Twitter and Congress. We find that "likes" are negative and significantly related to the number of bills voted in favor of. However, we find a heterogeneous propensity to

vote bills in favor if the "like" is given to an opponent. Our results can be rationalized by "likes" to coalition mates being signals of group loyalty instead of political agreement. On the other hand, "likes" to opponents would work as costly signals of ideological agreement as proposed in our public choice model. The implications of our results are related to voters' ability to distinguish politicians' epistemic impartiality, an important condition for reaching political agreement, as suggested by (Taylor & Bosworth, 2020). Another implication of our work is related to the idea that Twitter can work as a Public Sphere in today's politics, which contradicts research that claims that Twitter is mostly a noisy system.

Notes

1. The empirical analysis of these political networks follows a revealed preference approach where politicians and voters' preferences could be characterized from their observed political behavior (Henry & Mourifié, 2013).
2. Harmon et al. (2019) is one exception that exploits seating rules in the European Parliament to show that sitting adjacently leads to more political agreement.
3. We understand cross-cutting voting as two political opponents favoring the same bill.
4. We explicitly acknowledge that a signal of affection in Twitter can be confound by other dynamic effects that link two politicians at some point in time. Consequently, as a minimum the relevance of our findings are related to Twitter as a new source of information.
5. A "retweet" is a re-posting of a Tweet (message) from another user in Twitter. A "follower" is someone that decides to receive the Tweets of another user.
6. We understand the public political debate in a Habermasian sense, this is, as a public sphere where different actors try to advance their positions trough communicative rationality.
7. Grant et al. (2010) empirically show that politicians behavior in Twitter is noisy as is mainly related to broadcasting than engaging in dialogue.
8. Technically speaking, Heckman and Snyder (1996) show that empirical spatial voting estimates can be seen as a voting application of the revealed preference theory.
9. The Constitution of 1980 was approved by a referendum held under the Dictatorship's supervision and later modified by democratic-elected president Ricardo Lagos Escobar in 2005. Even though Lagos Escobar introduced several reforms to the Constitution, it was never considered a completely new one.
10. La Nueva Mayoría (New Majority) was an offset of the center-left coalition Concertación de Partidos por la Democracia, a new coalition of center-left and left parties supporting the presidential candidacy of Michelle Bachelet in the 2013 election. It included some political parties that did not participate from government in the Concertación, like the Chilean Communist Party
11. Fábrega et al. (2018) suggest that the student protests of 2006 and 2011 are early signs of their measured political polarization.
12. The 2020 Chilean national referendum was held in Chile on October 25th. The referendum asked whether a new constitution should be drafted, and whether it should be drafted by members elected directly for this purpose, or by a mixed body, made up in halves by currently sitting members of Congress and directly elected citizens. The "Approve" side won with 78% agreeing to draft a new constitution. On how the new text should be written, 79 choose the entire newly elected body.
13. This idea was introduced by (Zhang et al., 2008) that calculated network's modularity using votes from the U.S. Congress. Intuitively, the modularity corresponds to an aggregated measure of the intra-coallition versus inter-coallition interactions. For more details see A.
14. Martin (2015) proposes that ideologies are not necessarily internally consistent. However, ideologies would provide a representation of political alliances, and more importantly, the nature of political opponents.
15. Hinich and Munger (1996) cites the case of the minimum wage debate analyzed by Friedman (1966). Political disagreement in this case can be easily disentangled into values, and different predictions over the effects on the poverty rate or the labor market.
16. The practical implication of this assumption is that, in our model, some politicians are, exogenously more ideologically flexible than others, regardless of their ideological positions.
17. The specific parameter assumptions that govern the electoral population are shown 11.
18. Until 2017 Chile had a modified D'Hondt system with two seats by electoral entity (Dow, 2001). It has been argued by this system forced bipartisanship trough the formation of two coalitions in order to maintain political stability (Riquelme et al., 2018)
19. In C we show that the assumed distribution of voters has implications that are related to violations of the median voter theorem. In our baseline case, some politicians have incentives to move toward the extremes of the political spectrum.
20. For a detailed description of our estimation see Appendix B
21. The field work last 2 months approximately.

22. This data has been used to analyze Chilean politics in the empirical Public Choice literature, see Bonilla et al. (2011).
23. In our model we specifically address this issue, offering an interpretation in term of the median voter theorem.
24. Our proposed method is explained in Appendix B
25. In our model, we specifically address this issue, offering an interpretation in term of the median voter theorem.
26. For a more detailed analysis of the sampled 28 politicians see Figure 2.
27. See A for more details.
28. The Louvain method is based on a greedy optimization method, while the Edge Betweenness algorithm is an iterative process based on betweenness centrality.
29. The decline in modularity of the network of votes in favor by June 2020 is related to the cross-party agreement of an emergency coronavirus plan.
30. Our results appear to be robust to the methodological choice of community detection algorithm.
31. The Opponent Opp variable is constructed based on party affiliation.
32. In unreported results, we find that our documented positive effect of "likes" between opponents leading to more agreement in Congress survives clustering standard errors by directed politicians' pairs, and time-undirected politicians' pairs.
33 In an unreported result we check that using an Ordered Probit to measure ideology in this context does not make the difference.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A. Network modularity

A network cluster (communities) is a region of the network that is strongly connected within and relatively sparsely connected to the rest of the network. The common way of measuring how well a subdivision of a network into clusters capture the modular structure of the network is by network modularity (M. E. J. Newman, 2006). Mathematically, the network modularity Q is given by:

$$Q = \frac{1}{2m}\sum_{i,j}(\mathrm{a}_{i,j} - \frac{\mathrm{k}_i\mathrm{k}_j}{2m})\delta(\mathrm{c}_i, \mathrm{c}_j) \tag{7}$$

where $\mathrm{a}_{i,j} = 1$ if nodes i and j are connected and $\mathrm{a}_{i,j} = 0$, otherwise. $m = \frac{1}{2}\sum_{i,j}\mathrm{a}_{i,j}$ is the total number of edges in the network and $\mathrm{k}_i = \sum_j a_{i,j}\delta(\mathrm{c}_i, \mathrm{c}_j) = 1$ only if nodes i and j are in the same community. Otherwise, $\delta(c_i, \mathrm{c}_j) = 0$.

Appendix B. Estimated Politicians Ideology

In this section, we propose a simple method for estimating politicians perceived ideology from public opinion surveys. The measure is constructed using a simple OLS regression:

$$\mathrm{Opinion}_{j,k} = \alpha + \beta_k\,\mathrm{Ideology}_j + \in_j \tag{8}$$

where $\mathrm{Opinion}_j$ captures how favorable is the opinion of surveyed j about politician k. Voters opinion is measured in a 1 (very bad) to 5 (very good) scale. $\mathrm{Ideology}_j$ measures the self-reported ideology of surveyed j. Parameters that describe politicians ideology in the model (μ σ) are obtained from the mean and standard error of coefficients β_k. In the right and left extremes we have politicians with ideologies of 1 and 5, respectively. Ideology of the other politicians are re-adjusted using coefficients presented in Figure 2 in order to have a supply of politicians that go from 1 (right) to 5 (left). In Figure B1 we show the estimated levels of politicians from the CEP public opinion study as of May 2009.[33]

Appendix C. Median Voter Theorem

A standard benchmark in the public choice theory is the Median Voter Theorem of Dow (1998). In Figure C1 we show that our calibration of voters introduces an incentive to some politicians to move toward the extremes. Contrarily, a normal distribution of voters' ideology (same mean and standard deviation) increases the incentives to move toward the center. This incentive is enhanced, if the population is more continuously distributed in the whole political spectrum.

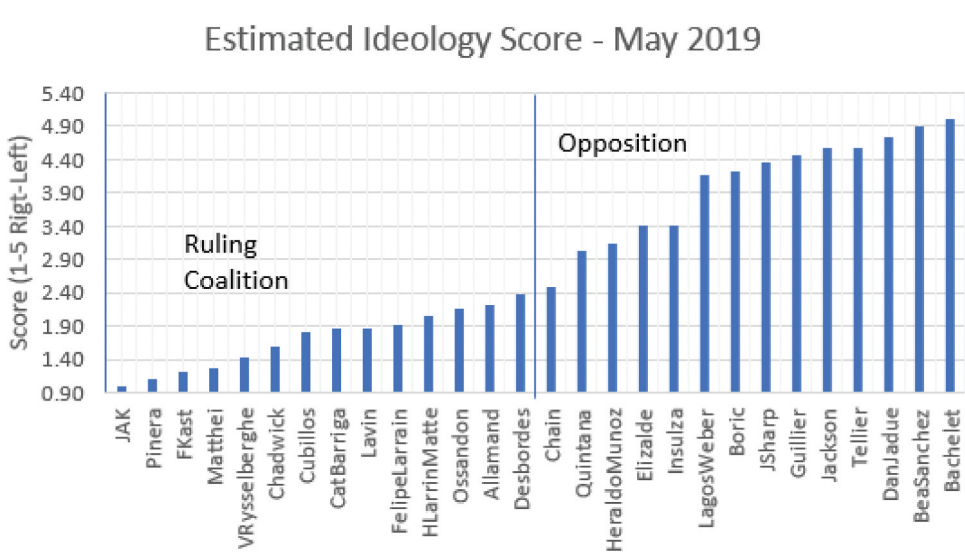

Figure B1. The figure plots the mean ideology of each politician in the model. Politicians are sorted from right to left.

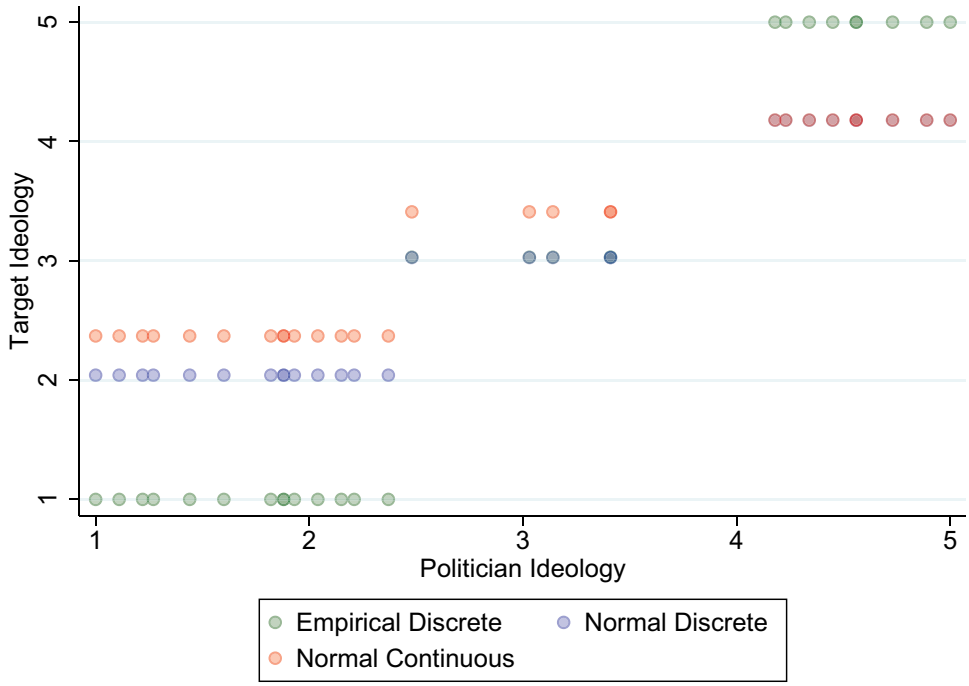

Figure C1. The figure shows how the electoral incentives are shaped by the distribution of voters. In the X-axis (Politician Ideology) is politicians' original ideology. In the Y-axis (Target Ideology), we have the ideology of the front-runner of the coalition for each politician. Empirical Discrete refers to the observed discrete distribution in the CEP opinion survey. Normal Discrete is a discrete distribution with the same mean and standard deviation of the voters' ideology. Normal Continuous corresponds to a continuous version of Normal Discrete.