

Raise your voice! Activism and peer effects in online social networks

Alejandra Agustina Martínez *

October 13, 2022

[Click here for the lastest version](#)

Abstract

This paper investigates peer effects on political activism through social media, specifically Twitter. To accomplish this, I combine tweets' and users' data to create a unique panel dataset with an explicit network structure. The Argentine abortion-rights debate, in which pro-choice and pro-life movements coexisted, is the context for this study. Theoretically, I develop a model of strategic interactions in a predetermined network. Considering that participants on equal or opposite movements may interact differently, the model allows for heterogeneous peer effects. Next, I test whether actions exhibit strategic substitutability or complementarity by empirically estimating the peer effects parameters. I provide a reduced-form analysis proposing a network-based instrumental variable. Results indicate the existence of solid complementarities in political activism; and homophily in the formation of Twitter's network.

Keywords: Political activism - Peer effects - Social networks - Social media

JEL Codes: D74, D85, P00, Z13

*Universidad Carlos III de Madrid, Spain. Email for correspondence: am@eco.uc3m.es. I am indebted to Antonio Cabrales for his advice throughout this project. I thank valuable feedback from seminar participants at Universidad Carlos III de Madrid, CAGE Centre - the University of Warwick, Royal Holloway University and Queen Mary University of London, Universidad Nacional de Buenos Aires, and Universidad Nacional de Tucumán.

1 Introduction

Do social interactions¹ affect individual behavior in the political arena? Is *political activism*, i.e., the participation in a social movement demanding political rights, a strategic action? Does it exhibit strategic substitutability or complementarity? A large body of literature in social sciences, including economics, speaks to the relevance of these questions. By analyzing political behavior in a novel context, this paper contributes to understanding its social drivers. Specifically, I examine peer effects on political activism through social media.

From a theoretical viewpoint, political activism was, and is, modeled as collective action problem or as a coordination game. In a collective action problem, individuals trade off public benefits and private costs to determine their participation in social movements, so actions are strategic substitutes, e.g., (Olson, 2009). On the other hand, activists' actions will exhibit strategic complementarity if social motives are present or information is imperfect, so a coordination device is needed, e.g., (Ostrom, 2000), (Edmond, 2013), and (Passarelli and Tabellini, 2017).

Despite its importance for theory and the lack of agreement on the strategic nature of activism, empirical research estimating how individuals respond to the activism of others is scarce. This scarcity is explained twofold: identifying peer effects is complex, e.g., (Manski, 1993), and their estimation requires specific data, which generally do not exist. For that reason, the large body of evidence of peer effects in political behavior comes from experimental methods, e.g., (Cantoni et al., 2019), (Hager et al., 2022), and (Perez-Truglia and Cruces, 2017), and just a few from observational data, e.g., (González, 2020). The observational data I use comes from the online world, specifically from the social media platform Twitter.

This paper aims to provide an empirical contribution to the literature studying political activism. Moreover, the case under study is interesting on its own: there is no one social movement but two happening simultaneously. Moreover, the political right that originates activism is controversial and normative. Specifically, I focus on the Argentinian abortion-rights debate. Congress discussed a bill to legalize abortion on demand in

¹By social interactions, I refer to interdependencies between individual actions and actions of their friends in a network.

2018 and 2020. During the debate, pro-choice and pro-life movements coexisted and actively sought participants. Notably, the online presence of the abortion-rights debate was vigorous.

Because of the nature of the subject, as well as heterogeneity in preferences and the observability of actions, social interactions are crucial to determining individual activism. Nevertheless, neither abortion-rights nor the Argentine context is too specific. There exist several controversial and normative topics; related to culture, social norms, religion, and policy; and diverse representations of online activism: #BlackLivesMatter, #MeToo, #LoveIsLove, #ClimateAction, and #GunControlNow, among others.

Theoretically, I conceptualize Twitter as a social network and posting tweets as a strategic interaction. I develop a model of peer effects in a predetermined but endogenous network. The model allows for differential effects between peers engaging in the same or opposite social movement. The model does not assume whether actions exhibit strategic substitutability or complementarity to be suitable for empirically testing.

In the data analysis, I combine tweets and users' information to generate a unique panel dataset in which links and actions are observable. The precise observation of Twitter's network makes this context ideal for estimating peer effects. The online platform, however, does not provide detailed individual characteristics. Then, I adapt the empirical approach proposed by peer effects literature to compensate for the data limitations.

In a reduced-form analysis, I estimate the peer effects parameters by proposing a network-based instrument. Following the empirical literature, e.g., (Bramoullé et al., 2009), the identification strategy relies on the partially overlapping network's property. Additionally, I take advantage of the longitudinal structure of the data to include individual fixed effects. These fixed effects control unobserved factors driving individuals' actions and network formation.

Results indicate the existence of strong complementarities in actions and homophily in the network formation. These results are robust to different specifications. While homophily is well documented in the literature on network formation, e.g., (Halberstam and Knight, 2016), the presence of strategic complementarities in activism is not as

frequent. In this regard, this paper contributes to the literature through its novel dataset, methodological approach, and findings.

The rest of the paper is organized as follows. Section 2 presents the model, and section 3 describes the data. Sections 4 and 5 present the peer effects estimates and the robustness checks, respectively. Section 6 concludes.

1.1 Literature review

Activism, polarization, and media (González, 2020) (Bursztyn et al., 2021) (Hager et al., 2022) (Halberstam and Knight, 2016) (Enikolopov et al., 2020) (Bursztyn et al., 2020) (Cantoni et al., 2019) (Cagé et al., 2022)

Peer effects in social networks (Goldsmith-Pinkham and Imbens, 2013) (Hsieh and Lee, 2016) (Hsieh et al., 2020) (Battaglini et al., 2021) (Canen et al., 2021) (Bramoullé et al., 2009) (Patacchini et al., 2017) (Brock and Durlauf, 2001) (Brock and Durlauf, 2003) (Bayer and Timmins, 2007) (Blume et al., 2011) (Ballester et al., 2006) (Jackson and Wolinsky, 1996) (Bramoullé et al., 2014)

1.2 Abortion-rights and activism in Argentina

In December 2020, the Argentine Congress legalized abortion on demand. Months earlier, the president sent the bill that became law. Nevertheless, it was not the first time the Argentine Congress studied that bill. Before that successful attempt, pro-choice activists² had put forward the same bill in Congress seven times. The first presentation was in 2005, but it never reached Congress.

The legislative branch in Argentina is bicameral, consisting of a Senate and a Chamber of Deputies. A bill put forward by a popular initiative has to go through three steps to become law. First, a subcommittee of the Chamber of Deputies receives it. The subcommittee has up to two years to send the bill to the Chamber of Deputies. If that happens, deputies study the bill. Finally, the Senate debates it. If both cameras pass the bill, it becomes law.

²Campaña Nacional por el Derecho al Aborto Legal Seguro y Gratuito, in Spanish.

In 2018, the abortion-rights bill reached Congress for the first time. Before, it never went further than the deputies' subcommittee. The Chamber of Deputies passed the bill in June 2018. The Senate rejected it, by a low margin of difference, in August 2018. Both cameras finally approved the law, as mentioned before, in December 2020. The previous year, 2019, was an electoral year in Argentina. As a result of the national elections, one-third of the seats in Congress changed. Most of the candidate's statements included the candidate's position on abortion-rights. Moreover, Congress members on seats in the two debates, 2018 and 2020, did not change their votes. This evidence suggests voters' important role in the abortion-rights bill's legislative process.

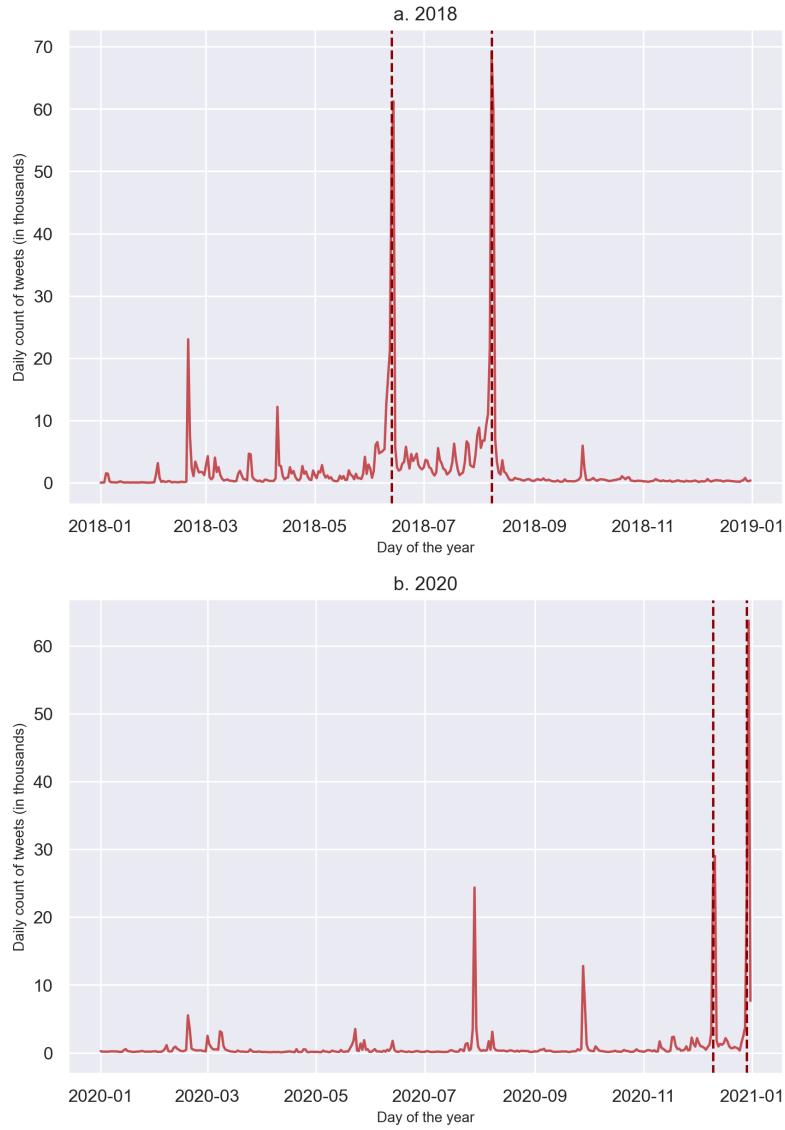
Abortion-rights were, and still are, a controversial aspect of reproductive rights in Argentina. The first evidence of this is the difficulty in passing the law. Yet, this is not particular to Argentina but common to many Latin American countries. Although they have different abortion regulations, most restrict abortion access. Only a few allow on-demand abortions.

The sustained mobilization of pro-choice activists and their counter-mobilization by pro-life activists is evidence of abortion-rights controversialism. Argentine campaigns for and against abortion legalization were actively seeking participants. They organized many public demonstrations over the period. Furthermore, they designed green and light-blue handkerchiefs to signal their advocacy. The usage of the pro-choice handkerchief crossed the Argentine borders. This green bandana became an international symbol of abortion-rights mobilizations.

Crucially, the online presence of pro-choice and pro-life activists was vigorous. Figure 1 shows the daily count of abortion-related tweets in 2018 and 2020. Twitter activity peaks coincide with days when Argentine Congress debated the bill.³ The online presence of the abortion debate on Twitter is the focus of this research. Appendix A.4 provides complementary information to this section.

³Specifically, days with legislative activity were June 13th and August 8th, 2018, and December 10th and 29th, 2020.

Figure 1: Abortion-related tweets in 2018 and 2020



Note: Daily count of abortion-related tweets, net of retweets, in the two years of debate, 2018 and 2020. Yellow dashed lines indicate days of legislative debate on the abortion bill.

2 Theoretical framework

I study a model of social interactions, where individuals choose their level of involvement in *online activism* related to a specific topic A in a *predetermined network*. The links between individuals included in the network represent mutually beneficial

relationships. Importantly, individuals care about the activism of individuals with whom they interact. Activism is characterized by its *intensity* and *sign*. Intensity relates to the individual effort in devoting time to being an activist. The sign of activism denotes whether the individual is an activist for or against cause A .

2.1 A model of peer effects in a network

Consider an online platform comprised of $n < \infty$ individuals, where $N = \{1, \dots, n\}$ is the set of individuals. Each user i has a specific peer group, P_i of size n_i . Let $G = [g_{ij}]$ be an $n \times n$ non-negative matrix representing the online links between those individuals. The (i, j) entry of G , denoted g_{ij} , equals $1/n_i$ if individuals i and j have a link and zero otherwise. I normalize diagonal elements of G to zero, so that $g_{ii} = 0 \quad \forall i \in N$. I assume links are undirected, i.e., $g_{ij} \neq 0$ if and only if $g_{ji} \neq 0$.

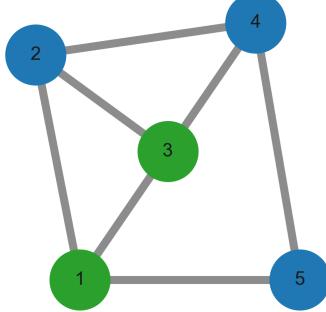
Conditional on the network structure and their preferences, individuals choose online activism, denoted by $a_i \in (-\infty, \infty)$. Importantly, $|a_i|$ denotes the intensity of activism and the sign of a_i indicates whether i is for or against A . Each individual i has an ideal point of online activism, denoted $\alpha_i \in (-\infty, \infty)$. Since the nature of interactions between individuals with equal-sign and opposite-sign ideal points may differ, I decompose the adjacency matrix G into two matrices, $H = [h_{ij}]$ and $K = [k_{ij}]$. Specifically, the matrix H includes all links in G between individuals of equal-sign ideal points, whereas K does it for opposite-sign. Thus, for any entry (i, j) of the matrices H , K , and G , the following hold:

$$\begin{aligned} h_{ij} &\equiv \mathbb{1}_{\alpha_i \times \alpha_j > 0} g_{ij} \\ k_{ij} &\equiv \mathbb{1}_{\alpha_i \times \alpha_j < 0} g_{ij} \\ G &\equiv H + K \end{aligned}$$

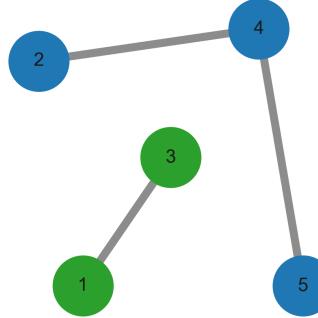
Figure 2 exemplifies the decomposition of the adjacency matrix G into the matrices H and K . Panels a, b, and c show the network representation of the matrices G , H , and K , respectively. In this example, $N = \{1, 2, 3, 4, 5\}$, $\alpha_i > 0$ for $i \in \{1, 3\}$ (green nodes), and $\alpha_i < 0$ for $i \in \{2, 4, 5\}$ (blue nodes). Thus, the network representation of H only includes links *within* the subsets $\{1, 3\}$ and $\{2, 4, 5\}$ whereas the network representation of K includes links *between* those subsets.

Figure 2: Decomposition of the adjacency matrix G

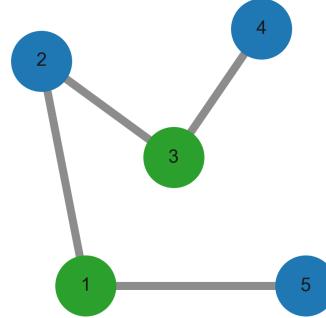
a. Network representation, adjacency matrix G .



b. Network representation, matrix H .



c. Network representation, matrix K .



Following the literature, e.g., (Ballester et al., 2006), (Bramoullé et al., 2014), I assume a linear quadratic specification for the utility of activism levels. Considering that activists for or against topic A may interact differently, the model allows for heterogeneous peer effects. The parameter β reflects peer effects when the sign of own and peers' ideal points coincide, i. e., individuals whose link belongs to matrix H . In contrast, γ measures peer effects when it differs, i. e., individuals whose link belongs to matrix K . Through this paper, I assume that $|\beta| < 1$ and $|\gamma| < 1$. Denoting any profile of activism levels by \mathbf{a} , the following function represents i 's utility:

$$u_i(\mathbf{a}, G) = u_i(\mathbf{a}, H, K) = \alpha_i a_i - \frac{1}{2} a_i^2 + \beta \sum_{j \in N} h_{ij} a_i a_j + \gamma \sum_{j \in N} k_{ij} a_i a_j \quad (1)$$

The first two terms of equation (1) reflect i 's private benefit and cost associated with her activism level. The third and fourth terms represent the heterogeneous social benefit or cost of changing an individual's action. Individuals play a non-cooperative game for the choice of the activism levels, conditional on the network structure. The equilibrium concept is Nash equilibrium. For any individual i , the Best Response function is given by:

$$a_i^{BR} = \alpha_i + \beta \sum_{j \in N} h_{ij} a_j^{BR} + \gamma \sum_{j \in N} k_{ij} a_j^{BR} \quad (2)$$

Denoting the ideal points vector by α , the system of Best Response functions in matrix notation equals:

$$\mathbf{a} = \alpha + \beta H \mathbf{a} + \gamma K \mathbf{a}$$

Provided $|\beta| < 1$ and $|\gamma| < 1$, $[I - \beta H - \gamma K]^{-1}$ exists, where I is the $n \times n$ identity matrix, the equilibrium is determined as:

$$\mathbf{a}(H, K) = [I - \beta H - \gamma K]^{-1} \alpha \quad (3)$$

The conditions for equilibrium for a fixed network structure G follow directly from the literature, see (Ballester et al., 2006) when actions are strategic complements and (Bramoullé et al., 2014) in the case of strategic substitutability. In Appendix A.1, I prove the condition for the invertibility of $[I - \beta H - \gamma K]$ and comment on the conditions for equilibrium uniqueness.

2.2 Discussion and extensions

Despite its simplicity, the model captures the following essential aspects of online interactions: (i) the network structure of social media platforms like Twitter, (ii) the interdependency between individuals' actions, and (iii) the potential heterogeneity in peer effects. In addition, the model is suitable for the empirical estimation of these heterogeneous peer effect parameters, which constitutes one of the main objectives of this project. In the context of peer effects on education, (Patacchini et al., 2017) also estimates a heterogeneous peer effects model, differentiating the parameters by the tenure of the links, i.e., long-lived vs. short-lived links. Consistently with my case study, the source of heterogeneity of peer effects in the model relates to the individuals' viewpoint on topic A .

According to the model predictions, any individual's activism level is a weighted sum of her preferences, α_i , and the average activism levels of her peers. If the social connections were not relevant to explaining activism, the optimal solution for any i is simply $a_i^* = \alpha_i$. If at least one parameter (β, γ) is different from zero, social interactions matter. As usual, a positive value of the equal-sign peers' activism parameter, β , indicates strategic complementarity in the intensity of activism, while a negative value indicates substitutability. In contrast, in the case of opposite-sign activism of peers, a positive value in γ reflects strategic substitutability in the activism intensity, and a negative value, complementarity. This interpretation responds to the fact that activism signs differ for them, whereas the intensity is always a positive value.

A limitation of this model is the assumption that the network is predetermined. In that sense, a possible extension would explicitly study network formation in addition to the strategic interactions. In that case, the game would be a two-stage game. Individuals first form their online social network and then choose their level of involvement in online activism. Taking equation (1) as a reference, the utility for i would be given by:

$$u_i(\mathbf{a}, G) = \alpha_i a_i - \frac{1}{2} a_i^2 + \beta \sum_{j \in N} h_{ij} a_i a_j + \gamma \sum_{j \in N} k_{ij} a_i a_j + \sum_{j \in N} g_{ij} \theta(i, j)$$

where the fifth term denotes i 's explicit preferences over the online network structure. The function $\theta(i, j)$ determines how much i values j as a peer in the network. It can depend on different variables, including i 's preferences for her and j 's degree, a measure of common interests, among others (see, for example, Hsieh et al. (2020)).

3 The Data

My primary data source is the platform Twitter. My goal is to understand how social interactions affect online activism. To do so, I need to construct a dataset in which both online activism and Twitter links are observable. The first challenge, in that respect, is to determine what online activism is. In the empirical analysis, I consider online activism as the number of abortion-related tweets posted by a user in a given period. Then, to measure online activism, the first step is building a *tweets' dataset*.

The second challenge is identifying social media users engaged in the Argentinian abortion-rights debate. Given that Twitter is a giant online network, I need to restrict my attention to a sub-sample of users to conduct the empirical analysis. My approach is to define the *initial nodes* of the network as the set of users who fulfill specific requirements. Then, by identifying these users, I construct the Twitter network where online activism is happening, which I name the *users' dataset*. By combining the tweets' and users' datasets, I create a panel dataset with an explicit network structure that allows me to conduct the empirical analysis. In the following paragraphs, I explain how I proceed to build and merge these two datasets.

To create the tweets' dataset, I first collect the set of abortion-related tweets from 2010 to 2020. I download all the tweets that contain at least one abortion-related hashtag.⁴ Twitter activists popularly used these pro-choice and pro-life hashtags to express their opinion. Further, activism through Twitter is often associated with specific hashtags, as documented in the literature.

The tweets' dataset includes all the replies and quotes to any of those tweets, but it excludes retweets. I exclude retweets from the analysis because “*retweet* \neq *endorsement*” is a popular statement on Twitter, so considering retweets would introduce noise in the classification of individuals as pro-choice or pro-life activists. I filter tweets according to their content and the account that posted them. The filtering criteria select Twitter accounts (i) with a positive number of links and (ii) which are not news outlets, organizations, or trending-topic trackers, among others. I further restrict the dataset to (i) tweets in Spanish and (ii) which do not correspond to an abortion-rights debate in another country where Spanish is an official language.

Moreover, in the empirical analysis, I restrict my attention to the years 2018 and 2020 for two reasons. This period concentrates most of the tweets. Additionally, it coincides with when the Argentine Congress debated the abortion-rights bill. The final tweets' dataset includes 2 million observations.

The primary variable of interest, named *online activism* and denoted by a_i , is the product of two terms. Activism intensity, as the daily count of abortion-related tweets

⁴Table 6 in Appendix provides the list of hashtags used in the Twitter query.

posted by any user, $|a_i|$; and activism sign, stating whether she is a pro-choice or pro-life activist.⁵ Following this procedure, I compute an integer-valued variable $a_i \in \{..., -2, -1\} \cup \{1, 2, ...\}$. I assign the value $a_i = 0$ for any user on the dates she did not post an abortion-related tweet. In that way, activism is a discrete variable in the interval $a_i \in \{..., -1, 0, 1, ...\}$.

To determine the activism sign, I need to classify all the tweets posted by a user on a given day as pro-choice or pro-life. To accomplish this, I proceed as follows. First, I classify a tweet as pro-choice (pro-life) if it only contains pro-choice (pro-life) hashtags. Then, I use a series of tuples of words to refine this classification. For example, if a tweet includes the hashtag “#AbortoLegal” (Legal abortion, in Spanish) and “murder,” it is classified as a pro-life tweet. Finally, I compute the average activism sign per day and individual and reclassify tweets to match the sign of this mean. This last step implicitly assumes individuals do not change their opinions in a short period, in this case, a day. Importantly, this procedure categorizes users into pro-choice and pro-life activist groups daily, allowing users to switch positions over more extensive periods. Nonetheless, I do not observe users switching between one and another movement.

Second, I construct the online network of Twitter users engaged in the Argentinian abortion-rights debate, which I previously named the users’ dataset. The first step is to define the *initial nodes* of the network. I consider as an initial node any user who fulfills the following conditions: (i) the user has posted at least one abortion-related tweet during the Congress debates in 2018 *and* 2020, (ii) she has less than 5.000 connections on Twitter, and (iii) the user provides geo-location information.

The upper bound imposed on connections works twofold. It limits the possibility of including celebrities, influencers, and politicians in the users’ dataset. The theoretical model presented in Section 2 may be unsuitable for these individuals as their incentives could differ from the rest of Twitter users. For instance, politicians’ tweets could obey their perceived probability of being elected, and celebrities may decide not to express their opinion to preserve their public image. Additionally, I impose this restriction by tractability. As mentioned, Twitter is a giant network, so restricting the number of connections alleviates the computational burden.

⁵A 10% of the initial nodes are pro-life activists, whereas the 90% missing is composed of pro-choice activists.

After applying this filtering criterion, the users' dataset contains 6.000 initial nodes. For any initial node, I download a list of her mutual connections, i.e., an account that is both a follower and a friend of that user. I define these users as *peers* in the empirical analysis. I restrict my attention to reciprocal links to recognize the different natures of unilateral and bilateral relationships. Finally, I download the list of mutual connections for randomly selected one percent⁶ of the peers in the network. I name them *peers of peers*. These three types of users, initial nodes, peers, and peers of peers, form the users' dataset.

For peers and peers of peers, I filter accounts with less than 5.000 connections for consistency. Furthermore, I only keep Twitter accounts whose creation date is 2018 or earlier. This condition is crucial, given how the Twitter API works. Its *follows-lookup endpoints* return connections on the day the request is made.⁷ Therefore, it is impossible to observe the Twitter network for a given time in the past. Applying the filtering criterion of creation date, I approximate the observed network as much as possible to the 2018-2020 network.

Additionally, I classify users according to their participation in abortion-right activism into three groups. A user is *in-activist* if she does not appear in the tweets' dataset. She is an *activist* if she appears in the tweets' dataset at least once and an *early activist* if she appears before the first Congress debate in June 2018. For any user i in a given day t , her *activity status* could be *active* or *inactive*, depending whether $a_{it} > 0$ or $a_{it} = 0$. Thus, an in-activist is a user whose activity status equals inactive for all the periods. At the same time, an activist is any user whose activity status equals active at least for some t . Thus, the categorization of peers into activist or in-activist is time-invariant, whereas the activity status of activist peers depends on the specific date t .

Table 1 summarizes initial nodes' degree distribution, i.e., their peer group size, and its decomposition into the categories of activists, early activists, and in-activists. On average, individuals have 412 reciprocal links, of which 97 are activists. Moreover, the set of activists who were active on a given date t , of size n_{it}^a , is a subset of the set of activists among peers, of size n_i^a . The latter category is the *relevant* in the model estimation. The last column of Table 1 reports that, on average, across time and individuals, initial

⁶For each i , I download that list for the closer natural number to $1\%n_i$.

⁷Twitter requests to this endpoint were made between December 2021 and February 2022.

nodes have 38 active peers. Combined with the full observability of Twitter links, the existence of small peer groups makes this context ideal for studying peer effects.

Table 1: Initial nodes' degree

	n_i	n_i^a	n_i^i	n_i^{ea}	mean n_{it}^a
Mean	412	97	315	45	38
St.Dev.	509	142	400	65	58
Min.	2	1	0	0	0
Median	250	45	188	19	13
Max.	4612	1723	3725	805	715
Individuals					5808

Note: n_i denotes the size of the peer group, whereas n_i^a , and n_i^i is its decomposition into the categories of activists and in-activists, respectively. n_i^{ea} is the size of the peer group classified as early activists. mean n_{it}^a is the mean size, across time, of activists' peers who were active at t .

Finally, I combine the tweets' and users' datasets previously mentioned to generate a *panel dataset* with an explicit *network structure*. For any initial node, I observe (i) the set of her first-degree connections, (ii) a sub-set of her second-degree connections, and (iii) the value of online activism for her and her observable connections. The panel dataset is balanced, each individual is an initial node, and the period is a day. In the empirical analysis, I use the dataset with observations for a one-week window centered on each day Congress debated the abortion-rights bill.

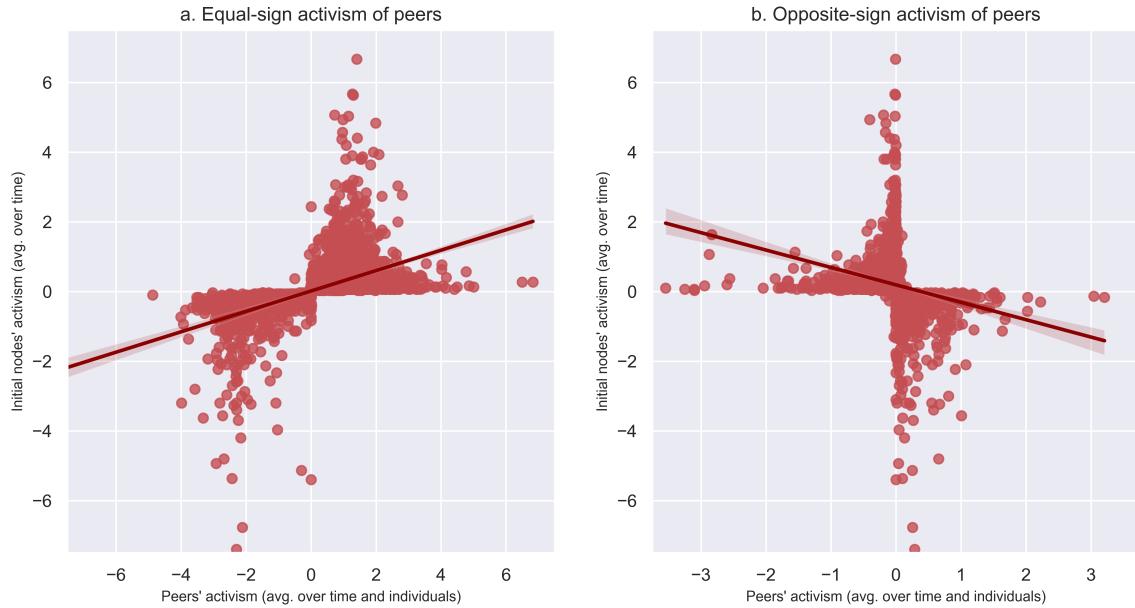
3.1 Descriptive statistics

Figure 3 presents correlations between initial nodes' activism and the average activism of their peers. The variable on the x-axis is the average of peers' activism over time and per individual. On the y-axis, the variable is the average over time of the initial nodes' activism. Panel A does it for equal-sign peers' activism, whereas Panel B is for opposite-sign peers' activism.

While the correlation between equal-sign peers' and own activism is positive, its analogous statistic for opposite-sign activism is negative. Since the intensity of activism

is its absolute value, the sign of the two correlations reflects a positive relationship between activism intensities. The intensity of pro-choice (pro-life) activism increases as it becomes more positive (negative). Therefore, a more intense opposite-sign peers' activism correlates positively with higher own activism.

Figure 3: Correlation between initial nodes' and peers' average activism.



In the two panels, points where activism of initial nodes is close to, but not equal to, zero reflect that the user was inactive on Twitter for some of the dates considered in the empirical analysis. Thus, the source of variation in initial nodes' activism is twofold: the intensity of their activism on the days they were active and the frequency of that activity status.

There is a notable difference between Panel A and B of Figure 3. While in Panel A, there are a few points in which peers' activism is close to zero, in Panel B, those points correspond approximately to a third of the total number of initial nodes.⁸ In other words, a third of the users considered as initial nodes do not have links with users whose (average over time) activism has the opposite sign. Moreover, this is true for initial nodes participating in both movements, pro-choice and pro-life. Nonetheless, two-thirds of the individuals are connected to users with opposing and aligned viewpoints on

⁸1636 out of the 5808 users.

abortion-rights. I interpret this as evidence against the existence of an *echo chamber*. A necessary condition for this phenomenon is the existence of a chamber: the segregation of users into like-minded groups.

Table 2: Descriptive statistics

	Mean	Median	Std. Dev.
Panel A: Pro-choice activists			Ind. 5225
activism	0.305	0.167	0.450
activism _{peer} ^{equal-sign}	0.913	0.837	0.539
activism _{peer} ^{opposite-sign}	-0.081	-0.024	0.204
active _{peer} ^{equal-sign}	25.746	9.133	39.056
active _{peer} ^{opposite-sign}	11.425	3.733	17.695
Panel B: Pro-life activists			Ind. 583
activism	-0.653	-0.300	1.055
activism _{peer} ^{equal-sign}	-1.545	-1.449	1.161
activism _{peer} ^{opposite-sign}	0.357	0.219	0.411
active _{peer} ^{equal-sign}	28.632	10.133	49.176
active _{peer} ^{opposite-sign}	12.317	5.133	18.383
Panel C: all activists			Ind. 5808
activist-peers _{ratio}	0.237	0.207	0.159
early activist-peers _{ratio}	0.448	0.455	0.165
activist-peers of peers _{ratio}	0.158	0.132	0.123
early activist-peers of peers _{ratio}	0.419	0.426	0.169

Note: all the variables in this table are averaged over time. The statistics presented, mean, median, and standard deviation, correspond to variables distribution by individuals. The activist-peers ratio is the number of activists among peers over the size of the peer group. The early activists-peers ratio is the number of early activists among activists' peers.

In this line, Table 2 presents complementary information. In Panel A and B, I summarize the main variables of the model, averaged over time. They include initial nodes' and peers' activism and the number of active peers. Panel A corresponds to the initial nodes classified as pro-choice activists, while Panel B does it for pro-life activists.

Lastly, Panel C presents descriptive statistics of the ratio of activist and early activist users in the peer groups and among peers of peers.

The mean of all the activism variables differs from zero over time and by individuals. Consistently with Figure 3, opposite-sign activism is the variable whose mean is closer to zero. On average, pro-choice initial nodes have 26 pro-choice and 11 pro-life active peers per day. For pro-life initial nodes, these numbers are 29 and 12. Therefore, around two-thirds of peers are like-minded activists, whereas one-third are not.

According Panel C, a 24% of users in the peer groups are activists, on average.⁹ The information in Table 2, jointly with Figure 3, suggests that users engaged in the abortion-rights debate are highly connected but not perfectly polarized into two groups. While the literature studying the existence of online echo chambers is inconclusive,¹⁰ there is evidence that activists and politically engaged users are highly connected through social media, e.g., (Halberstam and Knight, 2016), and (Larson et al., 2019). Accordingly, the description of this context is consistent with *homophily* in Twitter's network, in the sense of being politically engaged but not necessarily sharing viewpoints.

Finally, Figure 4 presents the correlation between initial nodes' activism and the ratio of early activists in her peer group. On the x-axis, the variable is the average over time of the initial nodes' activism. The y-axis variable is the proportion of early activist peers over the number of activist peers. According to Table 2, on average, 24% of peers are activists, and 45% among those are early activists. As Figure 4 shows, the differential exposure of initial nodes to early activism is a source of variation in the data (at the individual level). Significantly, the exposure to early activism varies for both pro-choice and pro-life initial nodes.

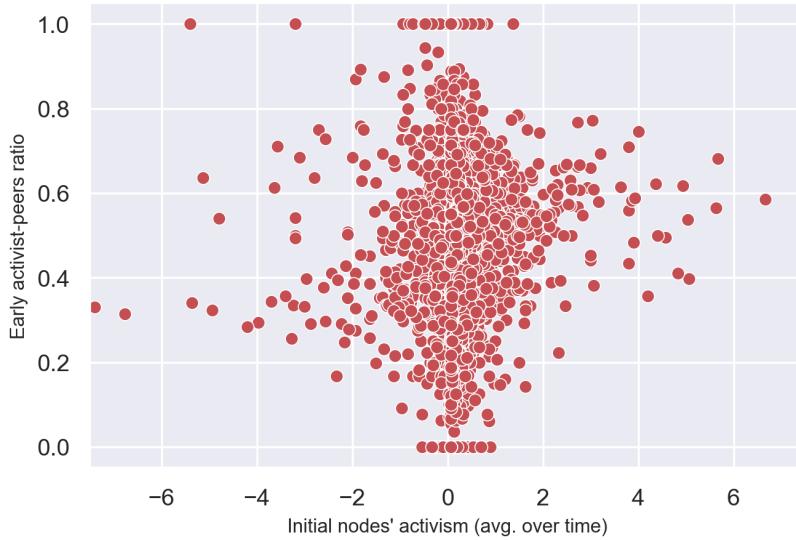
As mentioned above, I define an early activist as any user who appears in the tweets' dataset before June 2018, the month of the first Congress debate on the abortion-rights bill. In that regard, I interpret early activism as a measure of persistence, even strength, in online activism. Further, having early activist peers could be considered a source of

⁹ Appendix A.2 provides further information and descriptive statistics, including the histograms of the variables in Table 2.

¹⁰ See (Levy and Razin, 2019) for a review.

information about the abortion-rights debate. Therefore, differential exposure to early activists may play a role in explaining peer effects.

Figure 4: Correlation between activism and the early activist-peers ratio.



4 Reduced-form analysis

In this section, I follow an instrumental variables approach to estimate the heterogeneous peer effect parameters. Consistently with 2, I estimate peer effects by contemplating links between like-minded users and users with opposite viewpoints on abortion-rights. The identification strategy relies on the *partially overlapping network's property*, which allows me to propose network-based instruments. In addition, and taking advantage of the longitudinal data structure, I include individual fixed effects to control for unobserved factors driving online activism and network formation.

Before discussing the identification strategy, a clarification is relevant. I estimate peer effects for a sub-sample of the Twitter population: those who posted abortion-related tweets during the legislative debates on the bill. Extrapolating the results of the estimation in this study to the entire Twitter population would require assuming that the peer parameters among users who participate and who do not participate are equal.

In other words, I estimate peer effects on the *intensive margin* of online activism. Although interesting, the estimation of peer effects on the participation decision, i.e., the *extensive margin* of activism, is out of the scope of this paper. That estimation would require detailed individual characteristics¹¹ as well as the observation of the entire Twitter population.

4.1 Estimation and identification

It is a well-known challenge in the peer effects literature to disentangle the mechanisms behind the interdependence-in-actions of individuals who interact together. In his seminal paper, (Manski, 1993) distinguishes three sources of this interdependence: contextual, endogenous, and correlated effects. The contextual (or exogenous) effect is the influence of exogenous peers' characteristics on an individual's actions. The endogenous peer effect relates to the impact of peers' actions on an individual's actions. Lastly, individuals and their peers may behave similarly due to sharing a common environment, which is a correlated effect.

One of the advantages of estimating peer effects when interactions are structured through a social network is that the peer group of any individual is specific to her. This makes the distinction between endogenous and exogenous effects possible, alleviating Manski's *reflection problem*, which arises when individuals interact in groups.

Even though I do not estimate contextual effects and, instead, I control for them by using individual fixed effects, network data is still crucial for empirically identifying the peer effects parameters. The reason is that the activism of peers on the right-hand side of the best-response function, equation (2), is endogenous, and to deal with this endogeneity problem, I use a network-based instrument.

Specifically, I rely on the *partially overlapping network's property* to estimate the peer effects parameters, see (Bramoullé et al., 2009) and (De Giorgi et al., 2010). Given that individuals interact in a social network, two connected individuals, i and j , have different peer groups, P_i and P_j . Importantly, the existence of *intransitive triads* helps to identify peer effects.

¹¹Matching Twitter data with other data sources at the individual level is against Twitter Developer Account's terms and conditions.

An intransitive triad between individuals (i, j, l) exist if for the pair of individuals (i, j) there exists an individual l who is connected to j but not to i . In simple words, from i 's perspective, l is a friend of her friend, j . Formally,

$$i \in P_j \quad \text{and} \quad l \in P_j \quad \text{but} \quad l \notin P_i$$

For any individuals i and j , I define $P_{j/i}$ as the set of individuals l who form intransitive triads with them. If i is an initial node and j is her peer, I use individuals on the set $P_{j/i}$ to instrument for peers' activism. Particularly, the proposed instrumental variables are the *daily ratios of equal-sign and opposite-sign active users* among those in $P_{j/i}$.

Given the available data, the following remark is essential. The instrument is the activity status of the peers of a 1% randomly selected sample of initial nodes' peers. That is, I observe the activity status from users included in the sets $P_{j/i}$ from a 1% of the peers $j \in P_i$. For a given date t and initial node i , I compute the ratio of equal-sign and opposite-sign active users as the proportions of those in the union of the observed sets, $P_{j/i,t}$.

To gain intuition about the identification strategy, recall the ratios of equal-sign and opposite-sign active users on the sets $P_{j/i,t}$ measure the daily exposure of peers $j \in P_i$ to online activism. The construction of these ratios depends on the randomly assigned observability of the sets $P_{j/i}$, generating an additional source of variation. Then, the observed ratios measure the exposure to online activism of 1% randomly selected peers $j \in P_i$.

The identifying assumption is, therefore, that the *activity status* of the observed peers of peers, $l \in P_j$, who are not directly connected to an individual, $l \notin P_i$, only affects her activism, a_i , through the activism of peers, $j \in P_i$.

In the context of the Chilean student movement, (González, 2020) proposes a similar instrument variables approach to estimate peer effects on protest participation. Nonetheless, there is a slight difference between the two approaches. I instrument the intensive margin of peers' activism by using a measure of the extensive margin of peers of peers' activism.

For any initial node i and day t , the parametric specification of the individual heterogeneity in equation (1) is:

$$\alpha_{it} = \alpha_x x_{it} + \alpha_{LD} + \alpha_i + \epsilon_{it}$$

where x_{it} is a set of covariates related to the tweet's popularity,¹² α_i is an individual fixed effect. α_{LD} is a dummy variable that takes value one when Congress debated the abortion-rights bill, i.e., on a legislative day, and zero otherwise. ϵ_{it} is an *i.i.d.* error term with variance σ^2 .

The reason I include individual fixed effects is twofold. First, to control for unobserved and time-invariant factors driving Twitter users' behavior and, among them, potential contextual effects. Working with Twitter data has the advantage of clear observability of links but at the cost of lacking detailed individual characteristics, which constitute the source of identification of exogenous peer effects.

Additionally, individual fixed effects control for correlated effects and unobserved factors driving the network formation. The underlying assumption is that such unobserved variables are time-invariant. The empirical literature on peer effects has addressed these threats to identification using network fixed effects. Compared to individual fixed effects, these are less restrictive, for instance, regarding the covariates that can be included in the estimation.

In the main specification of the model, I do not include network fixed effects because of the difficulty of interpreting the parameters that result from the model estimation in which individual and network fixed effects are included. However, in appendix A.3, I show my results are robust to their inclusion.

4.2 Results

Table 3 presents the peer effects estimates. Columns (1)-(2) correspond to the Fixed Effects model (FE), whereas columns (3)-(4) present the results of the Instrumental Variables approach (IV-FE). Panel A includes all the observations for one-week windows centered on the legislative days,¹³ so the panel is balanced. In Panel B, I restrict my

¹²Daily average of likes, retweets, quotes, and replies.

¹³Except for December 29th, 2020, which window ends on January 1st, 2021.

attention to observations with non-zero values of initial nodes' activism. In all the specifications, results indicate the existence of complementarities in online activism.

Table 3: Peer effects in online activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
Panel A: Balanced Panel			Obs. 174238	
activism _{peer} ^{equal-sign}	0.194*** (0.014)	0.134*** (0.011)	0.564*** (0.020)	0.376*** (0.025)
activism _{peer} ^{opposite-sign}	-0.181*** (0.044)	-0.178*** (0.044)	-0.146 (0.134)	-0.428*** (0.130)
Panel B: Unbalanced Panel			Obs. 27652	
activism _{peer} ^{equal-sign}	0.350*** (0.038)	0.288*** (0.037)	1.000*** (0.087)	0.852*** (0.139)
activism _{peer} ^{opposite-sign}	-0.376* (0.157)	-0.387* (0.159)	-0.568* (0.237)	-0.765** (0.265)
Controls	X		X	
LegDays FE	X		X	

Note: Standard errors clustered by individuals in parenthesis. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes a value of 1 when Congress debated the abortion-rights bill and 0 otherwise. Panel A: Balanced panel dataset, daily observations for one-week periods centered on legislative days. Panel B: Unbalanced panel dataset, only considering non-zero values of initial nodes' activism. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

Coefficients of equal-sign activism levels are positive and significant. For instance, FE estimates in column (1) indicate that a 1-tweet increment on the equal-sign activism of peers increases initial nodes' activism by 0.19 tweets, on average. Coefficients of opposite-sign activism levels are negative and significant, except for column (3), in which the estimate is insignificant. However, this regression corresponds to the simplest IV model without controls nor legislative days fixed effects. When those are included, the estimate becomes significant. An increase of 1-tweet in the activism intensity of peers participating in the opposite online protest increases own activism by 0.18 tweets,

according to column (1).

The comparison between FE and IV-FE estimates suggests that complementarities are more substantial when estimated by the IV approach. The difference in magnitude between FE and IV estimates is in line with the fact that these estimators compute different average treatment effects (ATE).¹⁴ But, importantly, the sign and significance of the estimates remain stable among specifications.

Based on the difference in magnitude between Panel A and B estimates, one can argue that the sample restriction to non-null activism values for initial nodes leads to overestimating peer effects parameters. The coefficients in Panel B are twice as large as the analogous estimates in Panel A. In the rest of the analysis, I focus on the balanced panel dataset, where activism includes days in which Twitter users were inactive.

4.3 Heterogeneity analysis

This section provides two exercises to illustrate how the estimates of peer effects depend on peer groups' characteristics. Table 4 presents the results of the first of them: when users' exposure to early activism is taken into account. I classify as an early activist any user who posted an abortion-related tweet before the first Congress debate. The ratio of early activists at each initial node's group of peers is a source of variation in the data. I interact this ratio with peer effects parameters to see if it is relevant for understanding peer effects. Specifically, *exposure* is a dummy variable that takes a value of one for the individuals whose ratio of early activists in the peer group is above the sample median, 21%, and of zero otherwise.

The results suggest the strategic complementarity between equal-sign activist peers increases as the exposure to early activism. Coefficients of the interaction between equal-sign activism and exposure are positive and significant across all specifications. Early activism captures some degree of persistence, perhaps strength, in online activism. As such, I interpret this result as evidence of a higher complementarity between peers more involved in the abortion-rights debate.

¹⁴IV estimates the local ATE, whereas OLS estimates the ATE over the entire population.

In contrast, there is no evidence of a differential effect of early activism exposure in the parameters of opposite-sign activism. Accordingly, strategic complementarity between peers engaged in opposite movements does not differ based on whether the peer is a persistent activist or a newcomer. However, the interaction coefficients are not precisely estimated, as can be seen by the size of the standard errors.

Table 4: Peer effects in online activism. Exposure to early activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
activism _{peer} ^{equal-sign}	0.095*** (0.010)	0.050*** (0.007)	0.462*** (0.030)	0.200*** (0.036)
exposure * activism _{peer} ^{equal-sign}	0.247*** (0.019)	0.217*** (0.017)	0.159*** (0.040)	0.251*** (0.039)
activism _{peer} ^{opposite-sign}	-0.107*** (0.023)	-0.094*** (0.021)	-0.381* (0.165)	-0.755*** (0.148)
exposure * activism _{peer} ^{opposite-sign}	-0.182 (0.107)	-0.215* (0.108)	0.378 (0.272)	0.425 (0.257)
Controls		X		X
LegDays FE		X		X

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset. Daily observations for one-week periods centered on legislative days. Exposure is a dummy variable that takes a value of 1 if the early active-peers ratio is above the sample median and 0 otherwise. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes a value of 1 when Congress debated the abortion-rights bill and 0 otherwise. Observations: 174238. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

The second exercise I perform is related to the homogeneity of the sign of peers' activism. One of the main messages of Figure 3 is that initial nodes differ in the composition of peer groups. Around one-third of the initial nodes have no peers with an opposing viewpoint on abortion-rights, whereas the other two-thirds have them. To consider this fact when estimating peer effects, I define *homog* as a dummy variable that takes a value of one for the individuals whose average over time of opposite-sign peers' activism is sufficiently small and of zero otherwise. Results from the estimation of peer

effects interacted with *homog* are presented in Table 5.

Table 5: Peer effects in online activism. Homogeneous and heterogeneous peer groups.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
activism _{peer} ^{equal-sign}	0.231*** (0.017)	0.175*** (0.015)	0.565*** (0.029)	0.368*** (0.034)
homog * activism _{peer} ^{equal-sign}	-0.076** (0.025)	-0.081*** (0.019)	-0.006 (0.041)	0.014 (0.040)
activism _{peer} ^{opposite-sign}	-0.165*** (0.042)	-0.162*** (0.043)	-0.066 (0.116)	-0.376** (0.118)
homog * activism _{peer} ^{opposite-sign}	-1.216*** (0.177)	-0.984*** (0.155)	-1.918 (1.974)	-1.475 (1.737)
Controls		X		X
LegDays FE		X		X

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. Homog is a dummy variable that takes a value of 1 if the average over time of opposite-sign activism is <0.025 in absolute value and 0 otherwise. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes a value of 1 when Congress debated the abortion-rights bill and 0 otherwise. Observations: 174238. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

The reason for performing this exercise is twofold. First, to check if those initial nodes with a homogeneous peer group are driving some of the results¹⁵ in Table 3. It does not seem to be the case, as the coefficients in Table 3 are comparable in sign, magnitude, and significance level to their analog in Table 5, for individuals with heterogeneous peer groups.

Additionally, by estimating peer effects conditional on group composition, it is possible to test the existence of an *echo* in the sub-group of initial nodes inside a *chamber*, i.e.,

¹⁵This robustness check is crucial in the OLS estimation of the opposite-sign peer effects since its estimation could be contaminated by the points on the vertical line of Figure 3. The magnitude of estimates corresponding to the interaction between homog and opposite-sign activism is consistent with this argument.

the ones with homogeneous peer groups. In this case, the coefficients of particular interest are the ones of equal-sign activism. If there is an echo effect, that estimate would be higher for the sub-sample of initial nodes with homogeneous peer groups. As seen in Table 5, the evidence does not support the existence of an echo-chamber phenomenon. The estimate for the interaction of peer effect and homog is negative but small in columns (1)-(2), and it becomes insignificant for the IV specifications.

5 Robustness checks

6 Conclusion

References

- Ballester, C., Calvó-Armengol, A., and Zenou, Y. (2006). Who's who in networks. wanted: The key player. *Econometrica*, 74(5):1403–1417.
- Battaglini, M., Patacchini, E., and Rainone, E. (2021). Endogenous social interactions with unobserved networks. *The Review of Economic Studies*.
- Bayer, P. and Timmins, C. (2007). Estimating equilibrium models of sorting across locations. *The Economic Journal*, 117(518):353–374.
- Blume, L. E., Brock, W. A., Durlauf, S. N., and Ioannides, Y. M. (2011). Identification of social interactions. In *Handbook of social economics*, volume 1, pages 853–964. Elsevier.
- Bramoullé, Y., Djebbari, H., and Fortin, B. (2009). Identification of peer effects through social networks. *Journal of econometrics*, 150(1):41–55.
- Bramoullé, Y., Kranton, R., and D'amours, M. (2014). Strategic interaction and networks. *American Economic Review*, 104(3):898–930.
- Brock, W. and Durlauf, S. N. (2003). Multinomial choice with social interactions.
- Brock, W. A. and Durlauf, S. N. (2001). Discrete choice with social interactions. *The Review of Economic Studies*, 68(2):235–260.

- Bursztyn, L., Cantoni, D., Yang, D. Y., Yuchtman, N., and Zhang, Y. J. (2021). Persistent political engagement: Social interactions and the dynamics of protest movements. *American Economic Review: Insights*, 3(2):233–50.
- Bursztyn, L., Egorov, G., and Fiorin, S. (2020). From extreme to mainstream: The erosion of social norms. *American economic review*, 110(11):3522–48.
- Cagé, J., Hervé, N., and Mazoyer, B. (2022). Social media and newsroom production decisions.
- Canen, N., Jackson, M. O., and Trebbi, F. (2021). Endogenous networks and legislative activity. Available at SSRN 2823338.
- Cantoni, D., Yang, D. Y., Yuchtman, N., and Zhang, Y. J. (2019). Protests as strategic games: experimental evidence from hong kong’s antiauthoritarian movement. *The Quarterly Journal of Economics*, 134(2):1021–1077.
- De Giorgi, G., Pellizzari, M., and Redaelli, S. (2010). Identification of social interactions through partially overlapping peer groups. *American Economic Journal: Applied Economics*, 2(2):241–75.
- Edmond, C. (2013). Information manipulation, coordination, and regime change. *Review of Economic studies*, 80(4):1422–1458.
- Enikolopov, R., Makarin, A., and Petrova, M. (2020). Social media and protest participation: Evidence from russia. *Econometrica*, 88(4):1479–1514.
- Goldschmidt-Pinkham, P. and Imbens, G. W. (2013). Social networks and the identification of peer effects. *Journal of Business & Economic Statistics*, 31(3):253–264.
- González, F. (2020). Collective action in networks: Evidence from the chilean student movement. *Journal of Public Economics*, 188:104220.
- Hager, A., Hensel, L., Hermle, J., and Roth, C. (2022). Political activists as free-riders: Evidence from a natural field experiment.
- Halberstam, Y. and Knight, B. (2016). Homophily, group size, and the diffusion of political information in social networks: Evidence from twitter. *Journal of public economics*, 143:73–88.

- Hsieh, C.-S. and Lee, L. F. (2016). A social interactions model with endogenous friendship formation and selectivity. *Journal of Applied Econometrics*, 31(2):301–319.
- Hsieh, C.-S., Lee, L.-F., and Boucher, V. (2020). Specification and estimation of network formation and network interaction models with the exponential probability distribution. *Quantitative economics*, 11(4):1349–1390.
- Jackson, M. O. and Wolinsky, A. (1996). A strategic model of social and economic networks. *Journal of economic theory*, 71(1):44–74.
- Larson, J. M., Nagler, J., Ronen, J., and Tucker, J. A. (2019). Social networks and protest participation: Evidence from 130 million twitter users. *American Journal of Political Science*, 63(3):690–705.
- Levy, G. and Razin, R. (2019). Echo chambers and their effects on economic and political outcomes. *Annual Review of Economics*, 11:303–328.
- Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The review of economic studies*, 60(3):531–542.
- Olson, M. (2009). *The logic of collective action*, volume 124. Harvard University Press.
- Ostrom, E. (2000). Collective action and the evolution of social norms. *Journal of economic perspectives*, 14(3):137–158.
- Passarelli, F. and Tabellini, G. (2017). Emotions and political unrest. *Journal of Political Economy*, 125(3):903–946.
- Patacchini, E., Rainone, E., and Zenou, Y. (2017). Heterogeneous peer effects in education. *Journal of Economic Behavior & Organization*, 134:190–227.
- Perez-Truglia, R. and Cruces, G. (2017). Partisan interactions: Evidence from a field experiment in the united states. *Journal of Political Economy*, 125(4):1208–1243.

A Appendix

A.1 A model of peer effects in a network

A.1.1 Invertibility of $[I - \beta H - \gamma K]$

In this section, I show the assumption $|\beta| < 1$ and $|\gamma| < 1$ is a sufficient condition for the existence of $[I - \beta H - \gamma K]^{-1}$, which allows me to write (3). The proof consists on demonstrating that provided $|\beta| < 1$ and $|\gamma| < 1$, the matrix $[I - \beta H - \gamma K]$ is a *strictly diagonally dominant* matrix. And then, apply the *Gershgorin's circle theorem* to argue that the matrix is non-singular.

A square matrix is said to be strictly diagonally dominant if, for every row, its diagonal entry is larger than the sum of the absolute values of the non-diagonal entries in that row. That is, A is strictly diagonally dominant if

$$|a_{ii}| > \sum_{j \neq i} |a_{ij}| \quad \forall i$$

The diagonal entries of $[I - \beta H - \gamma K]$ are equal to 1, whereas the non-diagonal entries are either $-\beta h_{ij}$ or $-\gamma k_{ij}$. So, this matrix is strictly diagonally dominant if

$$\begin{aligned} 1 &> \sum_{j \neq i} |\beta h_{ij}| + \sum_{j \neq i} |\gamma k_{ij}| \quad \forall i \\ 1 &> |\beta| \sum_{j \neq i} h_{ij} + |\gamma| \sum_{j \neq i} k_{ij} \quad \forall i \end{aligned}$$

Where the second step follows from properties of absolute value and the fact that the entries of H and K are non-negative. Furthermore, as $G = H + K$, and G is row-normalized, it holds that

$$\sum_j h_{ij} + \sum_j k_{ij} = \sum_j g_{ij} = 1 \quad \forall i$$

Then, the left-hand side of the above inequality is a linear combination of $|\beta|$ and $|\gamma|$, and the condition of $|\beta| < 1$ and $|\gamma| < 1$ is sufficient to guarantee the inequality holds.

A.1.2 On the uniqueness of equilibrium

A.2 Data

A.2.1 Descriptive statistics

This section complements information presented at 3. Figure 5 shows the correlation between initial nodes' activism and the ratio of activists over the total number of users in her peer group. As can be seen, the Figure 6 characterize the behavior of the variables activism and peers' activism.

Figure 5: Correlation between activism and the active-peers ratio.

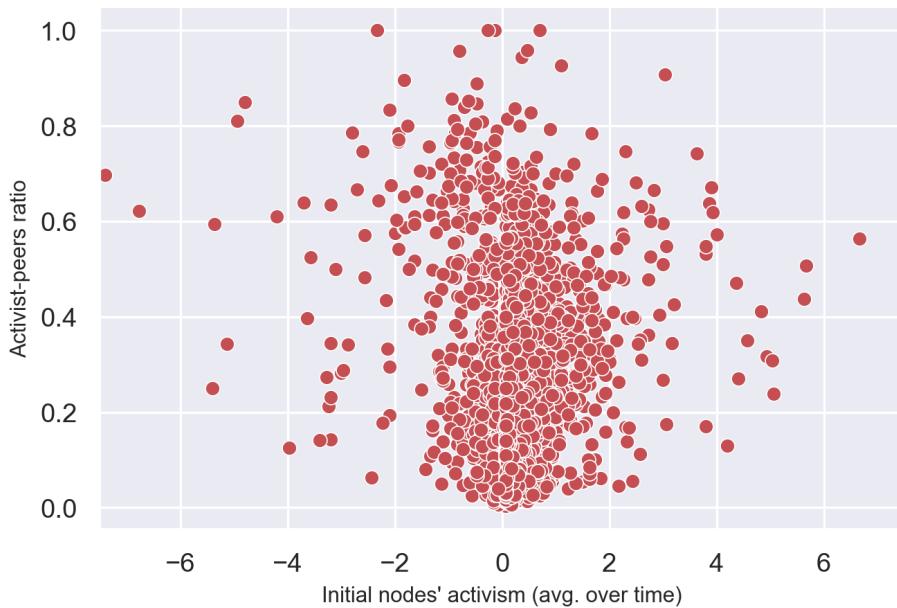


Figure 6: Histograms of average activism levels of initial nodes and their connections.

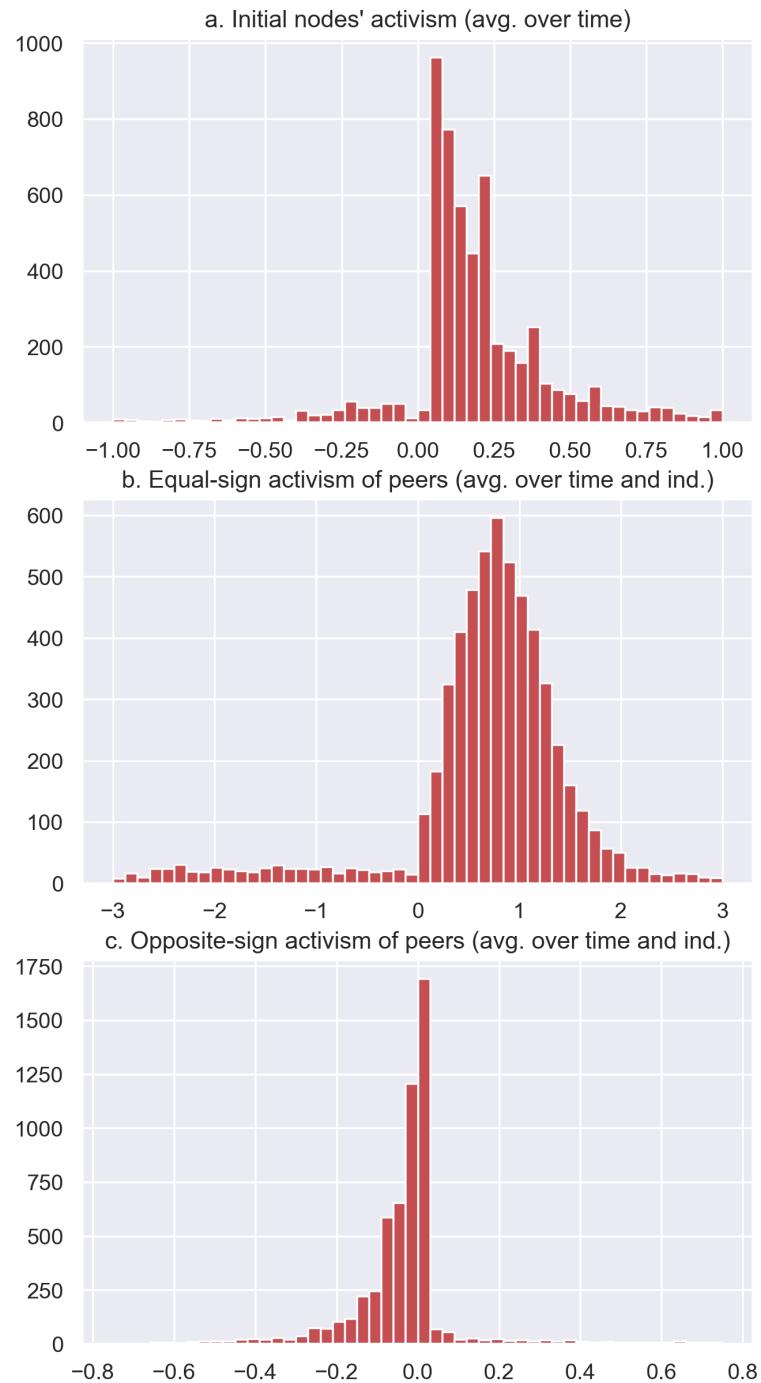


Figure 7: Histograms of active connections (avg. over time). Pro-choice initial nodes.

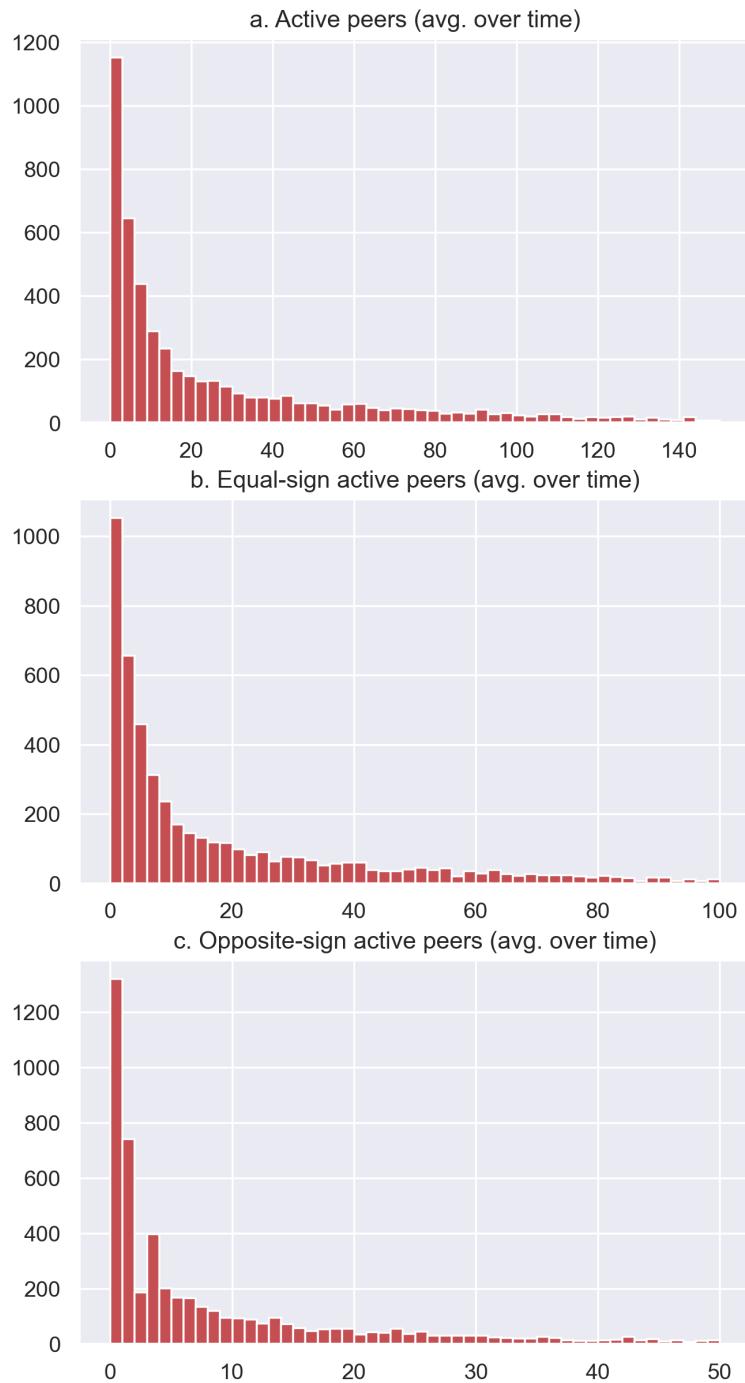
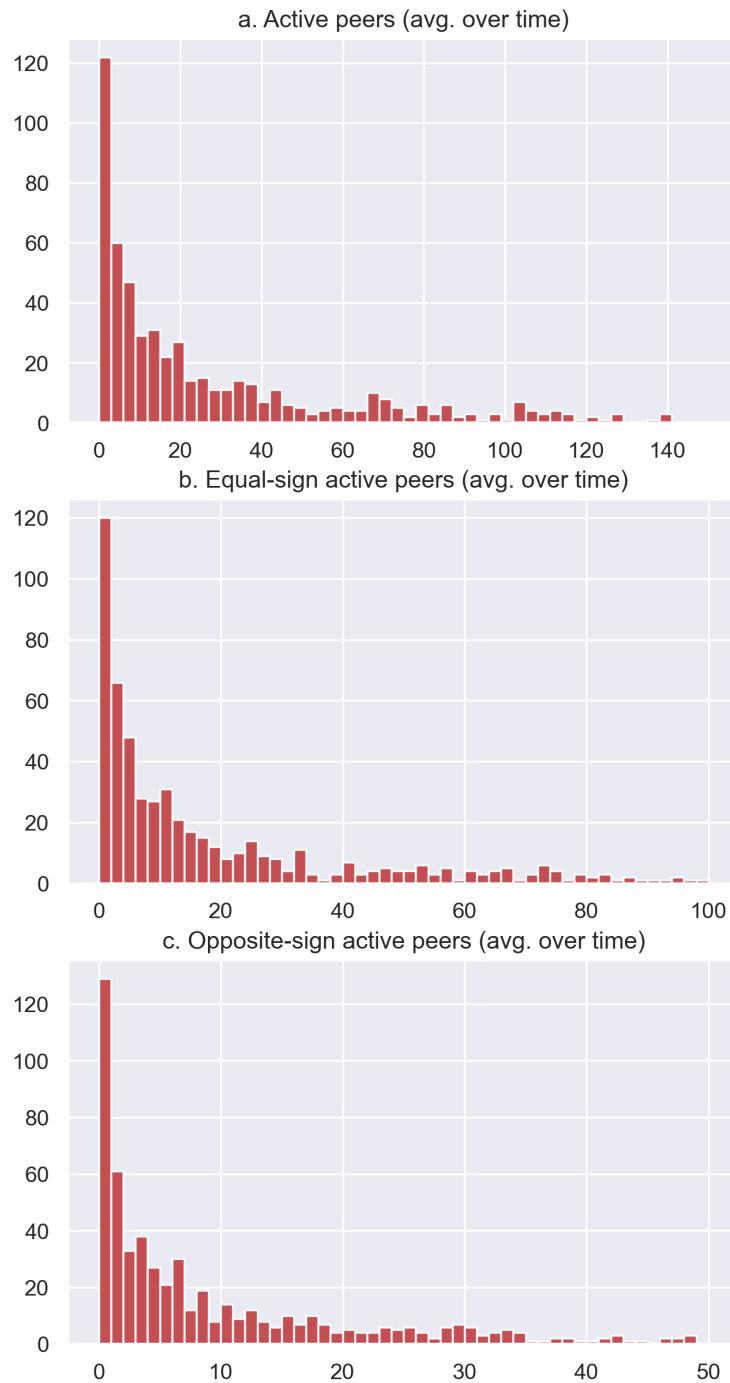


Figure 8: Histograms of active connections (avg. over time). Pro-life initial nodes.



A.2.2 Twitter data collection

Twitter is an online platform that allows users to publish short messages, of a maximum of 140 characters, on their profiles. Notably, the presence of politicians, celebrities, and public figures on Twitter is significant.

In January 2021, Twitter launched an Academic Research product track, which enables researchers to access all v2 endpoints. Notably, the *Twitter Search API v2* gives access to the entire history of public conversations and not only recent tweets. For more information about the academic track on Twitter, follow [this link](#).

I collected Twitter data with the command line tool and Python library, twarc2.

Tweets collection To collect tweets, I relied on the *v2 full-archive search endpoint*. I constructed the Twitter query to include all the tweets in Spanish, net of retweets, which include at least one of the hashtags present in Table 6.

User data collection To collect Twitter data relative to users, I relied on the *follows lookup endpoints*. For any user of interest, I requested the list of her friends (following) and followers. To obtain mutual connections, I intersected these lists.

Table 6: List of hashtags considered in the Twitter query.

Pro-choice hashtags	Pro-life hashtags
#AbortoLegalYa	#ArgentinaEsProvida
#AbortoLegal	#ArgentinaProVida
#AbortoLegalSeguroyGratis	#AbortoCero
#AbortoLegalYSeguro	#DefendamosLaVida
#AbortoLibre	#LegaloIllegalelAbortoMataIgual
#AbortoVoluntario	#MarchaPorLaVida
#AbortarEnPandemia*	#NoAlAborto
#EsLey*	#OlaCeleste
#GarantizarDerechosNoEsDelito	#PañueloCeleste
#IVE	#SalvemosLasDosVidas
#LaOlaVerde	#SalvemosLas2Vidas
#MareaVerde	#SalvenALos2
#PañueloVerde	#SiALaVida
#QueSubaLaMarea	#SoyProvida
#SeraLey	#TodaVidaVale
#UnaConquistaFeminista*	

Collection date: September 2021. *For 2020 only.

A.3 Reduced-form estimates

A.3.1 Adding network fixed effects

In this section, I add network fixed effects to the estimation presented in section 4. Specifically, I apply the local network transformation proposed by (Bramoullé et al., 2009) to the variables activism and peers' activism. The following tables are analogous to the ones in the main text.

Table 7: Peer effects in online activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
Panel A: Balanced Panel			Obs. 174238	
activism _{peer} ^{equal-sign}	0.125*** (0.011)	0.069*** (0.008)	0.548*** (0.035)	0.288*** (0.042)
activism _{peer} ^{opposite-sign}	-0.259*** (0.048)	-0.244*** (0.047)	-0.218 (0.148)	-0.584*** (0.145)
Panel B: Unbalanced Panel			Obs. 27652	
activism _{peer} ^{equal-sign}	0.135*** (0.035)	0.078* (0.033)	0.832*** (0.185)	0.353 (0.341)
activism _{peer} ^{opposite-sign}	-0.456** (0.148)	-0.453** (0.149)	-0.751* (0.315)	-1.256** (0.431)
Controls	X		X	
LegDays FE	X		X	
Network FE	X	X	X	X

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes a value of 1 when Congress debated the abortion-rights bill and 0 otherwise. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

As can be seen, the main results of section 4 are robust to the inclusion of network fixed effects. In some specifications, this inclusion makes the estimates of opposite-sign peers' activism larger in absolute value, with higher statistical significance levels.

Table 8: Peer effects in online activism. Exposure to early activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
activism _{peer} ^{equal-sign}	0.078*** (0.010)	0.035*** (0.006)	0.452*** (0.035)	0.176*** (0.041)
exposure * activism _{peer} ^{equal-sign}	0.134*** (0.019)	0.098*** (0.016)	0.173* (0.069)	0.181** (0.066)
activism _{peer} ^{opposite-sign}	-0.126*** (0.026)	-0.110*** (0.024)	-0.399* (0.168)	-0.789*** (0.148)
exposure * activism _{peer} ^{opposite-sign}	-0.275** (0.097)	-0.289** (0.097)	0.276 (0.283)	0.289 (0.264)
Controls		X		X
LegDays FE		X		X
Network FE	X	X	X	X

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset. Daily observations for one-week periods centered on legislative days. Exposure is a dummy variable that takes a value of 1 if the early active-peers ratio is above the sample median and 0 otherwise. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes value 1 when Congress debated the abortion-rights bill and 0 otherwise. Observations: 174238. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

Table 9: Peer effects in online activism. Homogeneous and heterogeneous peers group.

	FE	IV-FE		
	(1)	(2)	(3)	(4)
activism _{peer} ^{equal-sign}	0.158*** (0.014)	0.105*** (0.012)	0.553*** (0.050)	0.272*** (0.058)
homog * activism _{peer} ^{equal-sign}	-0.070*** (0.019)	-0.071*** (0.014)	-0.211 (0.198)	-0.165 (0.186)
activism _{peer} ^{opposite-sign}	-0.228*** (0.047)	-0.220*** (0.047)	-0.123 (0.137)	-0.514*** (0.141)
homog * activism _{peer} ^{opposite-sign}	-0.663*** (0.143)	-0.424** (0.135)	-3.819 (3.030)	-3.838 (2.858)
Controls		X		X
LegDays FE		X		X
Network FE	X	X	X	X

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. Homog is a dummy variable that takes a value of 1 if the average over time of opposite-sign activism is <0.025, in absolute value, and 0 otherwise. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes value 1 when Congress debated the abortion-rights bill and 0 otherwise. Observations: 174238. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

A.3.2 Changing the instrument

In this section, as in section 4, I follow an Instrumental Variables approach to estimate peer effects, relying on the partially overlapping network's property. For any individuals i and j , let $P_{j/i}^{ea}$ be the set of individuals k who (i) form *intransitive triads* with them, and (ii) are *early activists* according to the definition in section 3. I use the average activism of individuals on the set $P_{j/i}^{ea}$ for all peers $j \in P_i$ as an instrument for activism of peers, those in P_i . The identifying assumption is that the activism of the sub-group of peers of peers who are early activists and are not directly connected to an individual only affects her activism through the activism of peers.

Table 10: Peer effects in online activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
Panel A: Balanced Panel			Obs. 174238	
activism _{peer} ^{equal-sign}	0.194*** (0.014)	0.134*** (0.011)	0.519*** (0.031)	0.381*** (0.038)
activism _{peer} ^{opposite-sign}	-0.181*** (0.044)	-0.178*** (0.044)	-0.233 (0.171)	-0.411* (0.167)
Panel B: Unbalanced Panel			Obs. 27652	
activism _{peer} ^{equal-sign}	0.350*** (0.038)	0.288*** (0.037)	1.291*** (0.256)	1.355** (0.445)
activism _{peer} ^{opposite-sign}	-0.376* (0.157)	-0.387* (0.159)	0.217 (0.609)	0.254 (0.826)
Controls	X		X	
LegDays FE	X		X	

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes value 1 when Congress debated the abortion-rights bill and 0 otherwise. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

Table 11: Peer effects in online activism. Exposure to early activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
activism _{peer} ^{equal-sign}	0.095*** (0.010)	0.050*** (0.007)	0.412*** (0.042)	0.215*** (0.043)
exposure * activism _{peer} ^{equal-sign}	0.247*** (0.019)	0.217*** (0.017)	0.160** (0.062)	0.225*** (0.054)
activism _{peer} ^{opposite-sign}	-0.107*** (0.023)	-0.094*** (0.021)	-0.299** (0.113)	-0.480*** (0.109)
exposure * activism _{peer} ^{opposite-sign}	-0.182 (0.107)	-0.215* (0.108)	0.081 (0.435)	-0.002 (0.402)
Controls		X		X
LegDays FE		X		X

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset. Daily observations for one-week periods centered on legislative days. Exposure is a dummy variable that takes a value of 1 if the early active-peers ratio is above the sample median and 0 otherwise. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes a value of 1 when Congress debated the abortion-rights bill and 0 otherwise. Observations: 174238. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

Table 12: Peer effects in online activism. Homogeneous and heterogeneous peers group.

	FE	IV-FE		
	(1)	(2)	(3)	(4)
activism _{peer} ^{equal-sign}	0.231*** (0.017)	0.175*** (0.015)	0.521*** (0.033)	0.393*** (0.039)
homog * activism _{peer} ^{equal-sign}	-0.076** (0.025)	-0.081*** (0.019)	-0.036 (0.094)	-0.070 (0.085)
activism _{peer} ^{opposite-sign}	-0.165*** (0.042)	-0.162*** (0.043)	-0.122 (0.094)	-0.268** (0.096)
homog * activism _{peer} ^{opposite-sign}	-1.216*** (0.177)	-0.984*** (0.155)	-6.570 (7.965)	-8.232 (7.363)
Controls		X		X
LegDays FE		X		X

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. Homog is a dummy variable that takes a value of 1 if the average over time of opposite-sign activism is <0.025, in absolute value, and 0 otherwise. Controls include the daily average of retweets, likes, replies, and quotes. LegDays is a dummy variable that takes a value of 1 when Congress debated the abortion-rights bill and 0 otherwise. Observations: 174238. Individuals: 5808. * p<.05, ** p<.01, *** p<.001.

A.4 Abortion-rights and activism in Argentina and the World

Argentine Congress debated a bill to legalize abortion on demand in 2018 and 2020. Specifically, days with legislative activity were June 13th and August 8th, 2018, and December 10th and 29th, 2020. Figures 9 and 10 show the geographic pattern of votes in the Chamber of Deputies and the Senate, the two cameras of the National Congress, in 2018 and 2020.

Previously, Argentina permitted abortion only in cases of rape or to save the mother's life. There existed a protocol called Legal Interruption of Pregnancy, Interrupción Legal del Embarazo (ILE) in Spanish, for these cases. The Health Ministry launched this protocol in 2015, but not all the Argentine provinces adhered to it.

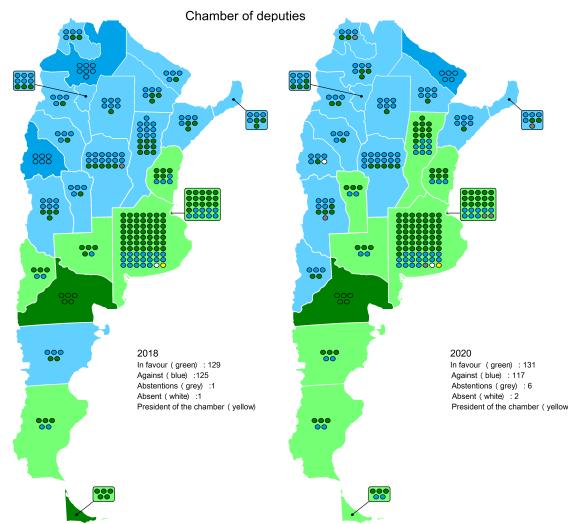


Figure 9: Votes in the Deputies Chamber by provinces, 2018 and 2020.

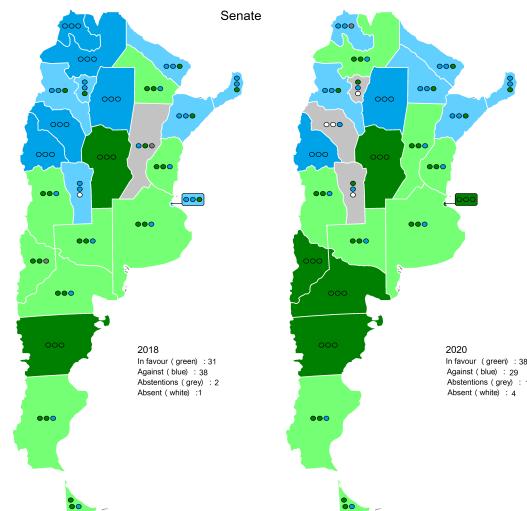


Figure 10: Votes in the Senate by provinces, 2018 and 2020.

While every country in Latin America has different regulations regarding abortion, in most of them, abortion access is restrictive, and only a few countries allow abortion on demand. Figure 11 presents the World map with information about abortion access in 2021.

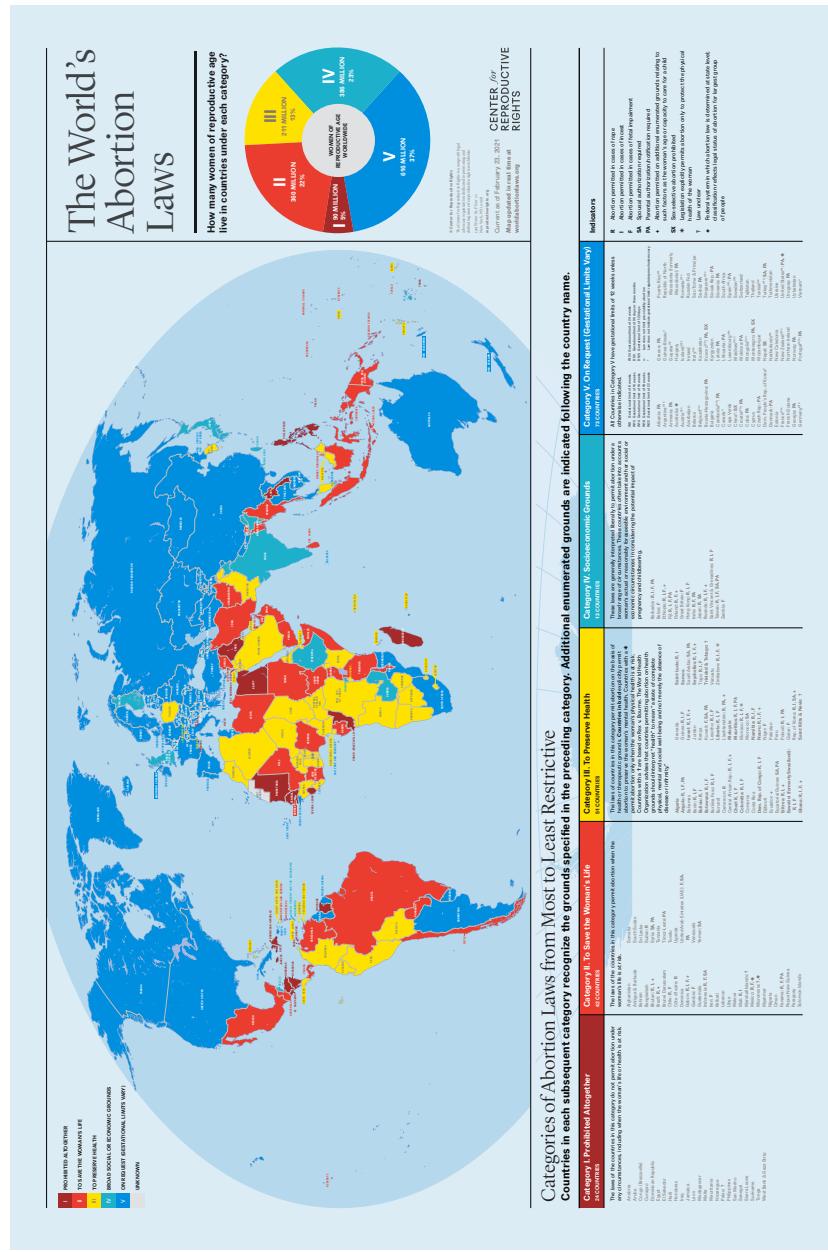


Figure 11: World's abortion laws map, 2021. Source: Center for Reproductive Rights.

Figure 12 shows the handkerchiefs designed by the pro-choice and pro-life activists, respectively, in Argentina. These bandanas became a symbol of the pro-choice and pro-life movements.



Figure 12: Pro-choice (left) and pro-life (right) handkerchiefs.