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

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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. As a robustness check, I estimate the model by Maximum Likelihood, controlling for network endogeneity. 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
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1 Introduction

Do social interactions[1] 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. Additionally, the case under study is interesting by itself: 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

[1] By 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.

As a robustness check, I provide a Maximum Likelihood Estimation, explicitly accounting for network endogeneity. To do so, I follow (Goldsmith-Pinkham and Imbens, 2013) and (Hsieh and Lee, 2016). To control for observed homophily, I construct a text similarity measure proposed by Yin and Wang (2014) and apply it to a tweet corpus of Twitter users categorized as activists.

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 by reduced-form and accounting for network formation, respectively. Section 6 concludes.

1.1 Literature review

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)

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)

Social networks - theory (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. The president sent the bill, which became law, months before. Nevertheless, it was not the first time the Argentine Congress studied that bill.

Before that successful attempt, pro-choice activists[2] 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.

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.

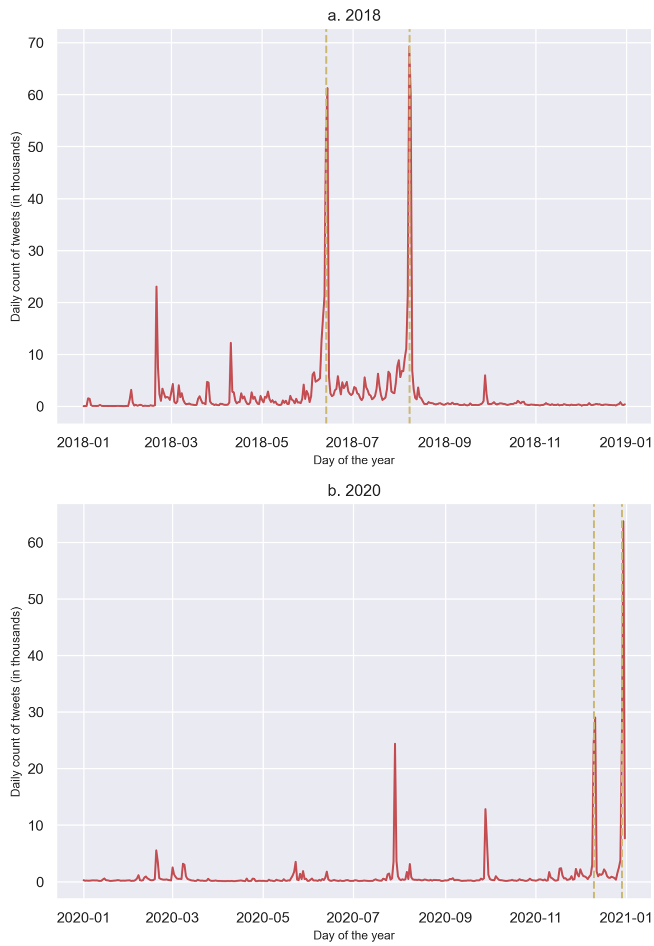
Both cameras finally approved the law, as mentioned before, in December 2020. The previous year, 2019, was an electoral year in Argentina. As a result of the national elections, one-third of the seats in Congress changed. Most of the candidate's statements included the candidate's position on abortion-rights. 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.

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

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.

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.

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

2 Theoretical framework

I study a model of social interactions, where individuals choose their level of involvement in online activism related to topic A in a *predetermined network*. The links between individuals represent mutually beneficial relationships. Importantly, these relationships require interactions, and individuals care about the activism of individuals with whom they interact.

Activism of a given individual is characterized by its *intensity* and *sign*. Activism-intensity relates to the individual effort in devoting time to being an activist. Activism-sign 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 individuals, where $N = \{1, ..., n\}$ is the set of individuals. Each user i has a specific peers' group, P_i of size n_i. Let $G = [g_{ij}]$ be an $n \times n$ non-negative matrix representing the online friendship of 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 their online activism level on topic A, denoted by $a_i \in (-\infty, \infty)$. Importantly, $|a_i|$ denotes activism intensity 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 links 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 friendships 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:

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

Following the literature, e.g., (Patacchini et al., 2017), I assume a linear quadratic specification for the utility of activism levels, allowing for heterogeneous peer effects. Specifically, the parameter β reflects peer effects when the sign of own and peers' ideal points coincide, while γ measures peer effects when it differs. 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:

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

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:

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

Denoting the ideal points vector by α, the model in matrix notation is:

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

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:

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

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

Although simple, the model captures the interdependency between individuals' actions, which constitute the main parameters to be estimated in the empirical section of this project. Any individual's activism level is a weighted sum of her preferences, α_i, and the 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. A positive value of the equal-sign peers' activism parameter, β, indicates strategic complementarity, while a negative value indicates substitutability. In the case of opposite-sign activism of peers, a positive value in γ reflects strategic substitutability, and a negative value, complementarity.

The main extension of this model would account for strategic network formation. In that case, the game is 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, utility for i is 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

3.1 Data description

My primary data source is the platform Twitter. My goal is to understand how social interactions affect online activism. To do so, I construct a network of social media users who are politically engaged. I build and combine a *tweets' dataset* and a *users' dataset* as follows.

First, I collect abortion-related tweets from 2010 to 2020. I download all the tweets that contain at least one abortion-related hashtag.[4] In the empirical analysis, I restrict my attention to the years 2018 and 2020 for two reasons. This period concentrates most of the tweets. Moreover, it coincides with the legislative activity days in the Argentine Congress.

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, (ii) which are no retweets, and (iii) which do not correspond to an abortion-rights debate in another country where Spanish is an official language. The final tweets' dataset includes 2 million observations.

Second, I construct the online network of Twitter users engaged in the abortion-rights debate. I define an *initial node* of the network as 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 any geo-location information.

The imposition of these conditions allows me to identify users engaged with the Argentinian debate on abortion-rights. The upper bound imposed on connections limits the possibility of including celebrities, influencers, and politicians in the users' dataset. The theoretical model presented in Section 2 is unsuitable for these Twitter users, and the analysis of their incentives is out of the scope of this paper. The dataset of initial nodes contains 6.000 Twitter users.

For any initial node, I download a list of her mutual connections, i.e., an account that is both follower and 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. Furthermore, given the size of the Twitter network, this restriction alleviates the computational burden of the model estimation.

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

Finally, I download the list of mutual connections for randomly selected one percent[5] 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 whose date of creation is 2018 or earlier. I impose the first condition for consistency. The second condition is crucial, given how the Twitter API works. Its *follows-lookup endpoints* return connections on the day the request is made.[6] Therefore, it is impossible to observe the Twitter network for a given time in the past. Applying this filtering criterion, 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 user is a user who is inactive all the periods, while an activist user is active at least for some t.

Table 1 summarizes initial nodes' degree distribution, i.e., the size of their peers' group, and its decomposition into the categories of activists, early activists, and in-activists. On average, individuals have 412 reciprocal links, but only 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. Combined with the full-observability of Twitter links, the existence of small peer groups makes this context ideal for studying peer effects.

Finally, I combine the two 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 and second-degree connections and (ii) all the abortion-related tweets she and her connections have posted during the period.

[5]For each i, I download that list for the closer natural number to $1\% n_i$

[6]Twitter requests to this endpoint were made between December 2021 and February 2022.

Table 1: Initial nodes' degree

	n_i	n_i^a	n_i^i	n_i^{ea}	min n_{it}^a	max n_{it}^a
Mean	412	97	315	45	15	63
St.Dev.	509	142	400	65	25	91
Min.	2	1	0	0	0	0
Median	250	45	188	19	4	26
Max.	4612	1723	3725	805	301	1080
Observations						5808

Note: n_i denotes the size of the peers' 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 peers' group classified as early activists. min n_{it}^a and max n_{it}^a are the minimum and maximum sizes, across time, of activists peers who where active at t.

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 her abortion-related tweets, $|a_i|$. And activism sign, stating whether she is a pro-choice or pro-life activist. In the

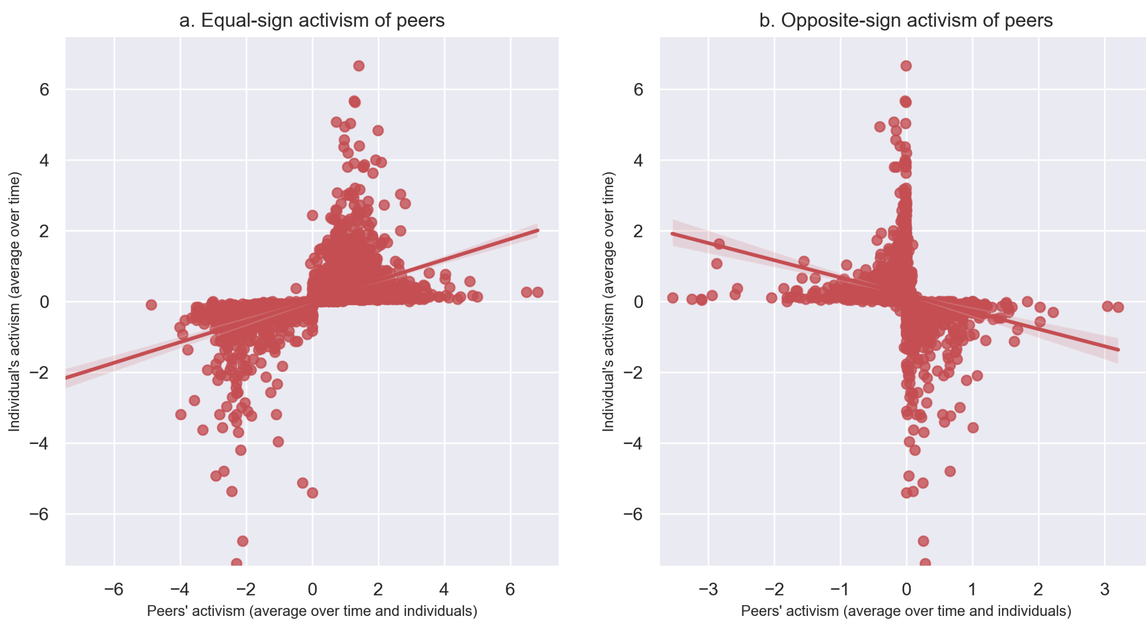
To construct activism, I classify tweets for and against abortion legalization, proceeding as follows. First, I classify a tweet as pro-choice, $a_i > 0$, or as pro-life, $a_i < 0$, if it only contains pro-choice or pro-life hashtags, respectively. Then, I use a series of tuples of words to refine this 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 per day and individual and reclassify tweets that differ from the mean. This last step implicitly assumes individuals do not change their opinions in a short period, in this case, a day.

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 initial node on the dates they did not post an abortion-related tweet. In that way, the panel dataset is balanced, and activism is a discrete variable in the interval $a_i \in \{..., -1, 0, 1, ...\}$.

3.2 Descriptive statistics

Figure 2 presents correlations between the activism of initial nodes and 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 initial nodes' activism. Panel a. does it for equal-sign peers' activism, whereas panel b. for opposite-sign peers' activism.

Figure 2: Correlation between own and peers' average activism levels.



While the correlation between equal-sign peers' and own activism is positive, its analogous statistic for opposite-sign activism is negative. Since activism intensity for pro-choice (pro-life) grows as activism value increases (decreases), both correlations reflect a positive relationship between activism intensities.

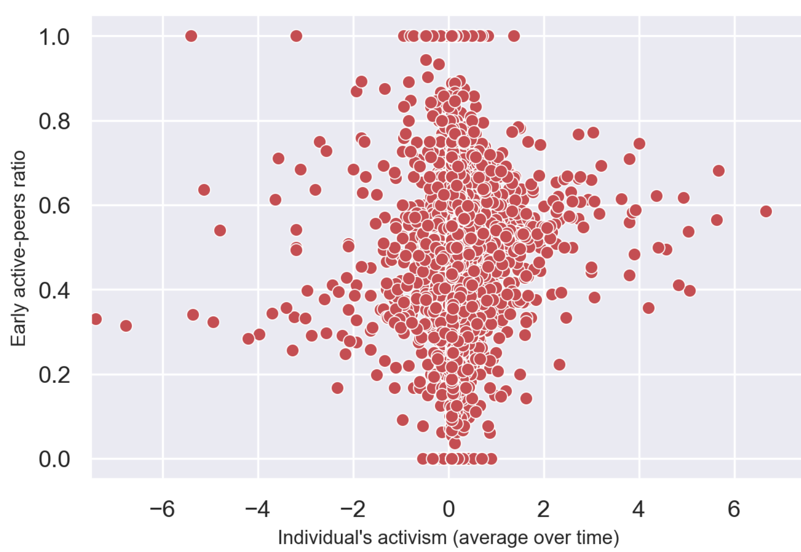
In the two panels, points where activism of initial nodes is close to, but not equal to, zero reflect that the user was inactive on Twitter for some of the dates considered in the empirical analysis.[7] Thus, the source of variation in initial nodes' activism is twofold: the intensity of their activism on the days they were active and the frequency of that activity status.

[7]One-week window centered on the days with legislative activity.

There is a notable difference between Panel a. and b. of Figure 2. While in Panel a., there are no points in which peers' activism is close to zero, in Panel b. those points exist and correspond approximately to a third of the total number of initial nodes. 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. This observation is consistent with *homophily* in the network formation of Twitter.

Figure 3 presents the correlation between initial nodes' activism and the ratio of early activists in her peers' group. On the y-axis, the variable is the average over time of initial nodes' activism. On the y-axis, the variable is the ratio of early activist peers over the number of activist peers. The differential exposure of initial nodes to activism is one of the sources of variation in the data at the individual level. In Appendix A.2, I show that the ratio of activist over the total number of peers behave similarly.

Figure 3: Correlation between activism and the early active-peers ratio.



4 Reduced-form analysis

In this Section, I follow an instrumental variables approach to estimate the peer effects parameters. As described in Section 3, data is structured as a balanced panel dataset. The individual individual variable is an initial node's identifier, whereas the time variable is a day.

By taking advantage of this data structure, I include individual fixed effects to control for unobserved factors driving online activism and network formation.

Before discussing the identification strategy, two clarifications are relevant. First, I estimate peer effects for a sub-sample of the Twitter population: those who posted abortion-related tweets during the legislative debates. 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 addition, I estimate peer effects on the *intensive margin* of online activism, which I previously called activism intensity. 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.[8]

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. In contrast, the endogenous peer effect relates to the impact of peers' actions on an individual's actions. Lastly, correlated effects account for the fact that individuals and their peers may behave similarly because they share a common environment.

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 fact alleviates Manski's *reflection problem*, which arises when individuals interact in groups and makes the distinction between endogenous and exogenous effects complex.

Even though I assume there are no contextual effects and I control for them by using individual fixed effects, network data is still crucial for empirically identifying the parameters of peer effects. The reason is that the activism of peers on the right-hand

[8] That estimation would probably require matching Twitter data with other data sources, which is against Twitter's terms and conditions.

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 such that $g_{ij} > 0$, have different peer groups, P_i and P_j. Importantly, the existence of *intransitive triads* helps to identify peer effects. 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. That is, $g_{il} = 0$ and $g_{jl} > 0$.

For any individuals i and j, I define $P_{j/i}$ as the set of individuals l who form intransitive triads with them. That is, $l \notin P_i$, and $l \in P_j$. If i is an initial node and j is her peer, i.e., $j \in P_i$, I use individuals on the set $P_{j/i}$ to instrument for peers' activism. Particularly, I use the daily *ratio 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 approach to estimate peer effects on protest participation. However, there is a subtle difference between the two approaches. While (González, 2020) focuses in the extensive margin of collective action, I use a measure of the extensive margin of peers of peers' activism to instrument for the intensive margin of peers' activism.

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

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

where x_{it} is a set of covariates related to the tweets popularity,[9] α_i is an individual fixed effect, $\alpha_{LegDays}$ is a dummy variable that takes value one when Congress debated the abortion-rights bill and zero otherwise; and ϵ_{it} is and *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.

[9] Daily average of likes, retweets, quotes and replies.

4.2 Results

Table 2 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,[10] so the panel is balanced. In Panel B, I restrict my 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 2: Peer effects in online activism.

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

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

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 OLS and IV estimates is in line with the fact that these estimators compute different average treatment effects (ATE).[11] 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.

[11] IV estimates the local ATE, whereas OLS estimates the ATE over the entire population.

4.3 Heterogeneity analysis

Table 3: Peer effects in online activism. Homogeneous and heterogeneous peers group.

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

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

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

5 Network formation

****In progress****

In this section, I develop a structural approach based on (Goldsmith-Pinkham and Imbens, 2013) and (Hsieh and Lee, 2016). The basic idea is that I can address the network endogeneity problem by studying network formation and outcome determination jointly. I model the network formation process via pairwise stability, while the outcome is specified following the model in Section 2.

5.1 Pairwise stability

The first assumption I make is that links are mutually beneficial. Two individuals must agree to form a link and will do so if and only if the net utility from the link is positive for each of them. Additionally, I assume this utility only depends on the characteristics of the two individuals. Formally, assume i's utility from the link (i, j) is:

$$U_i(j) = \gamma_0 + \gamma_x |x_i - x_j| + \gamma_\xi |\xi_i - \xi_j| + \epsilon_{ij} \tag{4}$$

where ϵ_{ij} has a logistic distribution, and (γ_x, γ_ξ) account for observed and unobserved *homophily.* If two individuals are peers, they must be similar in observed, unobserved characteristics, or both. The probability of observing the link (i, j) is:

$$P_{ij} = \mathrm{pr}\left(U_i(j) > 0, U_j(i) > 0|x\right) = p_{ij} \cdot p_{ji}$$

The network structure is endogenous if the unobserved characteristics of each additionally affect her behavior, i.e., if ξ_i affects i's activism. In that case, it is required to estimate jointly network formation and outcome determination. The conditional likelihood function is:

$$\mathcal{L}\left(\alpha, \beta, \gamma \mid \mathbf{a}, \mathbf{G}, \xi, \mathbf{x}\right) \quad = \quad \mathcal{L}_{\text{activism}}\left(\alpha, \beta \mid \mathbf{a}, \mathbf{x}, \xi\right) \times \mathcal{L}_{\text{network}}\left(\gamma \mid \mathbf{G}, \xi, \mathbf{x}\right)$$

where the first term is the likelihood function of the activism determination, and the second term is its equivalent for the network.

5.2 Observed homophily: a NLP approach

One of the main challenges in estimating the network formation process in this setting is the lack of data to do so. The universe of Twitter data includes information about tweets, user (self) description, and connections, among others. However, it does not have any other information about individuals, allowing researchers to identify them.

To overcome this challenge, I rely on Natural Language Processing (NLP) techniques. For each individual in the 'users-dataset' previously defined, I download a corpus of 0-100 tweets posted in a period before the first Congress debate on the abortion bill. I process these corpora of text employing a Short Text Topic Modeling Technique (STTMT) introduced by Yin and Wang (2014). Finally, I estimate a measure of similarity between these corpora to be included in the observed homophily term of equation (4).

6 Conclusion

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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 inequality holds if and only if $|\beta| < 1$ and $|\gamma| < 1$.

A.1.2 On the uniqueness of equilibrium

A.2 Data

A.2.1 Descriptive statistics

This section complements information presented at 3. Figure 4 shows the correlation between initial nodes' activism and the ratio of activists over the total number of users in her peers' group. Additionally, Table 5 and Figure 5 characterize the behavior of the variables activism and peers' activism.

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

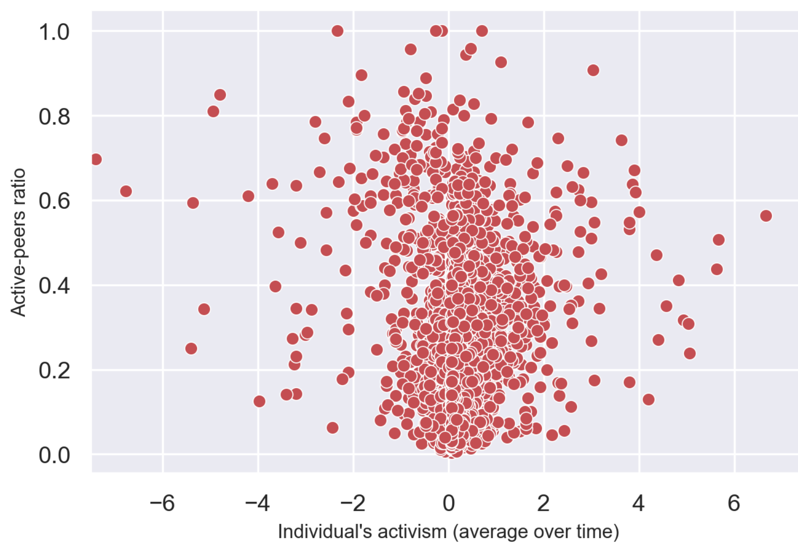
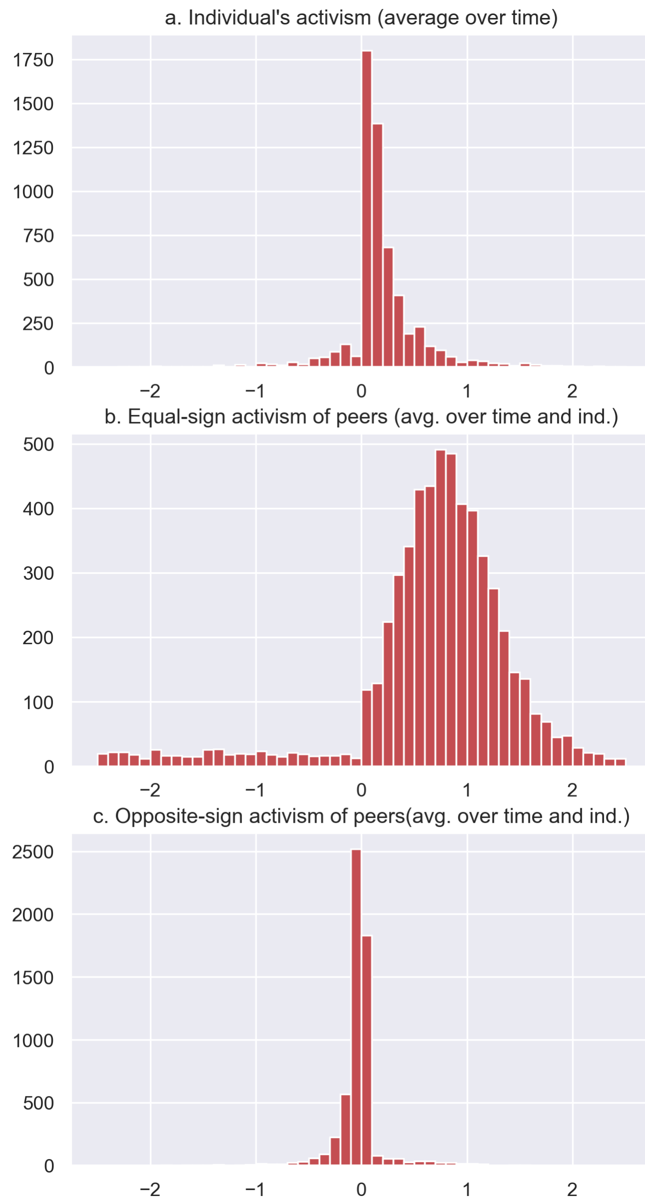


Table 5: Descriptive statistics

Variable	Mean	Median	Std. Dev.
activism	0.31	0.17	0.45
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	0.91	0.84	0.54
$\text{activism}_{\text{peer}}^{\text{opposite-sign}}$	-0.08	-0.02	0.20
activism	-0.65	-0.30	1.05
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	-1.55	-1.45	1.16
$\text{activism}_{\text{peer}}^{\text{opposite-sign}}$	0.36	0.22	0.41
$\text{act/inact}_{\text{peer}}$	0.24	0.21	0.16
$\text{early act/act}_{\text{peer}}$	0.45	0.45	0.16
$\text{act/inact}_{\text{peer of peer}}$	0.16	0.13	0.12
$\text{early act/act}_{\text{peer of peer}}$	0.42	0.43	0.17
Observations			5808

Figure 5: Histograms of average activism levels of initial nodes and their connections.



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.

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

Pro-choice hashtags	Pro-life hashtags
#AbortoLegalYa	#ArgentinaEsProvida
#AbortoLegal	#ArgentinaProVida
#AbortoLegalSeguroyGratuito	#AbortoCero
#AbortoLegalYSeguro	#DefendamosLaVida
#AbortoLibre	#LegaloIlegalelAbortoMataIgual
#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.	

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.

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
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	0.125***	0.069***	0.548***	0.288***
	(0.011)	(0.008)	(0.035)	(0.042)
$\text{activism}_{\text{peer}}^{\text{opposite-sign}}$	-0.259***	-0.244***	-0.218	-0.584***
	(0.048)	(0.047)	(0.148)	(0.145)
Panel B: Unbalanced Panel				Obs. 27652
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	0.135***	0.078*	0.832***	0.353
	(0.035)	(0.033)	(0.185)	(0.341)
$\text{activism}_{\text{peer}}^{\text{opposite-sign}}$	-0.456**	-0.453**	-0.751*	-1.256**
	(0.148)	(0.149)	(0.315)	(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. Homogeneous and heterogeneous peers group.

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

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Table 9: Peer effects in online activism. Exposure to early activism.

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

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
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	0.194***	0.134***	0.519***	0.381***
	(0.014)	(0.011)	(0.031)	(0.038)
$\text{activism}_{\text{peer}}^{\text{opposite-sign}}$	-0.181***	-0.178***	-0.233	-0.411*
	(0.044)	(0.044)	(0.171)	(0.167)
Panel B: Unbalanced Panel				Obs. 27652
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	0.350***	0.288***	1.291***	1.355**
	(0.038)	(0.037)	(0.256)	(0.445)
$\text{activism}_{\text{peer}}^{\text{opposite-sign}}$	-0.376*	-0.387*	0.217	0.254
	(0.157)	(0.159)	(0.609)	(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. Homogeneous and heterogeneous peers group.

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

Table 12: Peer effects in online activism. Exposure to early activism.

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

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 6 and 7 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.

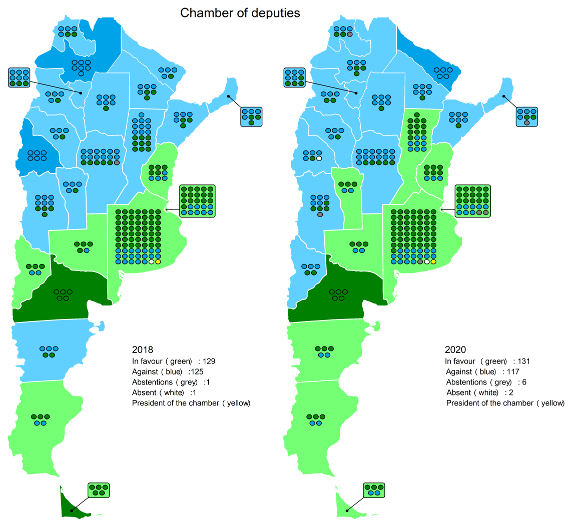

Figure 6: Votes in the Deputies Chamber by provinces, 2018 and 2020.

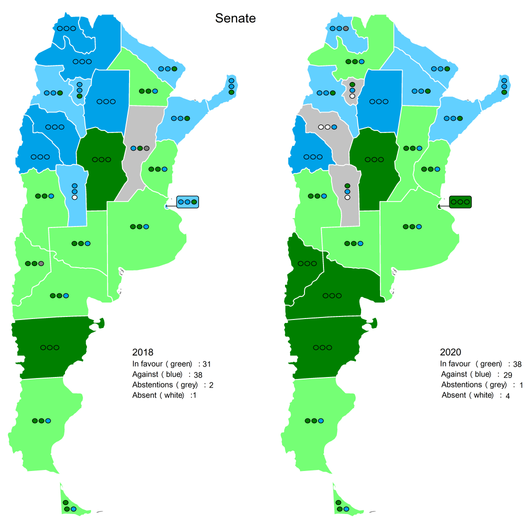

Figure 7: Votes in the Senate by provinces, 2018 and 2020.

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 8 presents the World map with information about abortion access in 2021.

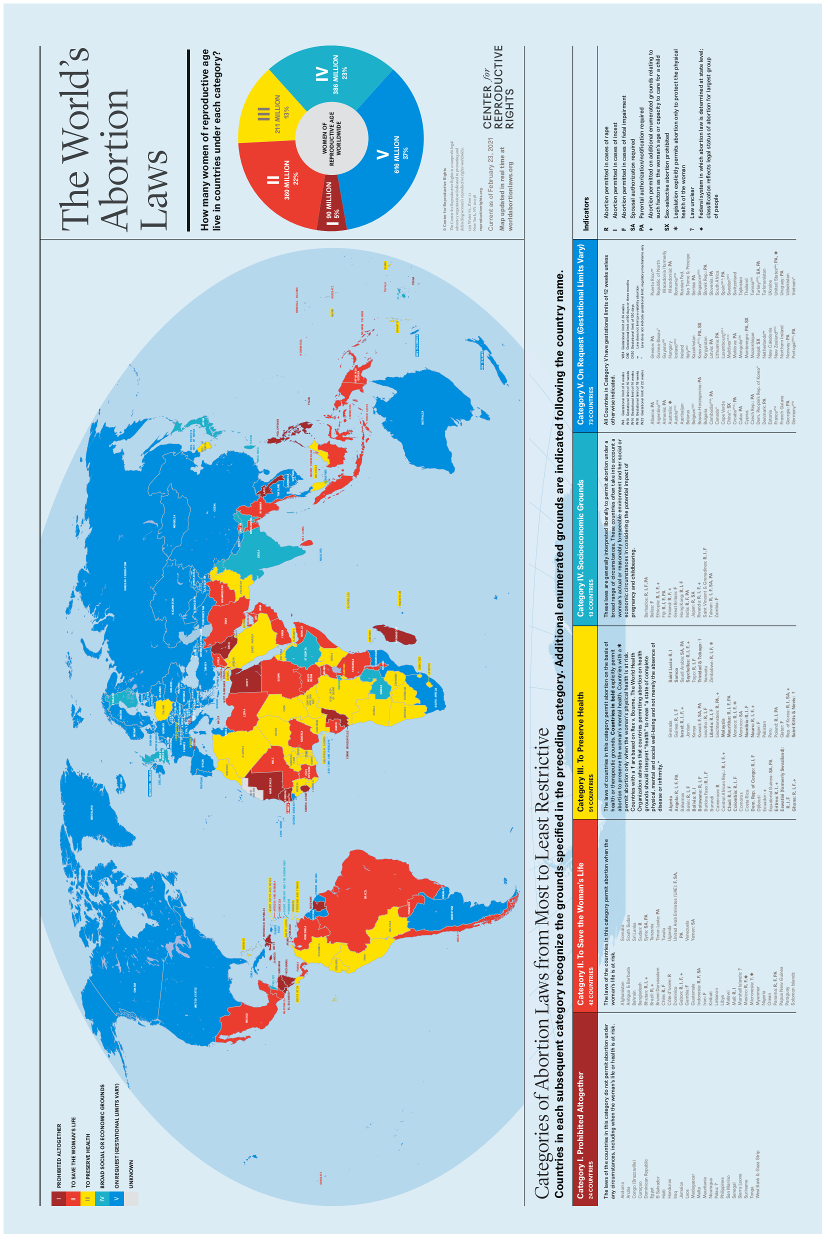

Figure 8: World's abortion laws map, 2021. Source: Center for Reproductive Rights.

Figure 9 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 9: Pro-choice (left) and pro-life (right) handkerchiefs.