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

Alejandra Agustina Martínez *

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**Abstract**

Do peers influence individuals' involvement in political activism? To provide a quantitative answer, I study Argentina's abortion rights debate through Twitter - the social media platform. Pro-choice and pro-life activists coexisted online, and the evidence suggests peer groups were not too polarized. I develop a model of strategic interactions in a network - allowing for heterogeneous peer effects. Next, I estimate peer effects and test whether online activism exhibits strategic substitutability or complementarity. I create a novel panel dataset - where links and actions are observable - by combining tweets' and users' information. I provide a reduced-form analysis by proposing a network-based instrumental variable. The results indicate strategic complementarity in online activism, both from aligned and opposing peers. Notably, the evidence suggests homophily in the formation of Twitter's network, but it does not support the hypothesis of an echo-chamber effect.

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

**JEL Codes:** D74, D85, P00, Z13

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# 1 Introduction

What is the influence of peers on individuals' engagement in *political activism*?[1] There is no straightforward answer to this question - related to a collective action problem. First, there is no theoretical agreement on the strategic nature of activism. Model assumptions on the utility function and information structure determine whether actions are strategic substitutes or complements[2] - Olson (2009), Ostrom (2000), Edmond (2013), Passarelli and Tabellini (2017). Second, empirical research of peer influence on political activism is scarce; some exceptions are Bursztyn et al. (2021), Cantoni et al. (2019), González (2020), and Hager et al. (2022). This scarcity is explained twofold: identifying the influence of peers in individual actions is complex (Manski, 1993) and estimating it requires specific data - including at least a rough approximation of social interactions. In a novel context, this paper contributes to the literature on collective action problems by examining *peer effects*[3] in political activism.

In this paper, I rely on data from Twitter, which provides an ideal context for studying peer effects in political activism. Social media platforms have created a new public sphere where individuals connect, interact, and communicate. As for Twitter, *hashtags* have become a default method to designate online collective thoughts, ideas, and claims. Among them are the ones advocating for social change - constituting the *online version of political activism*: #BlackLivesMatter, #MeToo, #LoveIsLove, #ClimateAction. Moreover, Twitter offers precise observability of online links and rich data on social interactions. Regarding the decision to follow an account, unilateral and bilateral ties exist. Users interact in several ways: by posting, replying, retweeting, and quoting tweets.

My approach to investigating how peers affect political activism focuses on understanding the *local and direct mechanism* - the influence of peers' actions - that drives *individual political behavior* and leads to a *global outcome* - a collective claim. To frame this question, I develop a theoretical model of peer effects in a network that explicitly assumes individuals care about their peers' activism. Then, I estimate the model by proposing a network-based instrumental

[1] I refer to political activism as the participation in a collective claim demanding political rights.

[2] Scholars usually frame collective action problems as a public good or a coordination game, leading to different implications about the strategic nature of actions.

[3] That is, the influence of peers' actions on individuals' actions.

variable. I rely on Twitter data to conduct the empirical analysis, and I focus on the *intensive margin* of political activism and *reciprocal ties*. I precisely identify peer groups and offer a quantitative measure of activism intensity, contributing to the literature on political activism. In addition, this paper contributes to the literature on peer effects by estimating them in a new and suitable environment - social media platforms.

I analyze activism surrounding the abortion rights debate in Argentina in 2018 and 2020. This debate is great for studying how social interactions shape individual activism for three main reasons. First, the abortion rights debate in Argentina was long-lived. Specifically, Congress debated a bill legalizing abortion on demand twice, in 2018 and 2020 - rejected in the former and passed in the latter. Second, pro-choice and pro-life activists coexisted on and offline; their activism persisted until the law's approval. The differential result of the 2018 and 2020 debates suggests voters' important role in the abortion rights bill's legislative process - as 2019 was an electoral year. Third, not only the political right that originates activism - abortion rights - is controversial and normative, but also actions are observable.[4] Altogether suggest peer activism might influence individuals.

I model social interactions as follows. I conceptualize Twitter as a social network and posting tweets as strategic interactions. Then, I develop a model of heterogeneous peer effects in a network. I assume links connecting activists are of two types: between individuals with aligned or opposing viewpoints on abortion rights. I allow for a differential influence of activist peers depending on the type of link. I do not impose additional assumptions regarding the strategic nature of activism, allowing me to empirically test the existence of substitutability or complementarity in online behavior.

The model estimates reveal the existence of strategic complementarity in online activism. Notably, this strategic complementarity comes from both aligned and opposing activist peers. The evidence suggests that the composition of the peer group plays a role in understanding individual activism. Remarkably, the exposure to *early activism*, approximated by the proportion of peers who were activists before the first Congress debate in 2018, is associated with a higher strategic complementarity, but only for like-minded activists. Early activism speaks to the

[4]That is, individuals can observe the activism of their peers.

tenure of peers' activism - if they are persistent activists or newcomers. As such, I interpret this result as a differential impact of activism tenure, depending on the link type, i.e., connecting aligned or dissident peers.

To conduct the empirical analysis, I recover Twitter's network where online activism happens. I build a longitudinal dataset of Twitter users where ties and actions are observable. The construction of this novel dataset involves two significant challenges - determining online activism and identifying social media users engaged in the abortion rights debate to recover their network. For the former, I define *online activism* as the product of two terms: its *intensity* - the daily count of abortion-related tweets posted by any user - and its *sign* - pro-choice or pro-life. My approach for the latter is defining an *initial node* of Twitter's network as any user who has posted at least one abortion-related tweet during each Congress debate - in 2018 *and* 2020. For any initial node, I define her *peer group* as the set of users who follow and are followed by the user - her reciprocal ties. In addition, I download the mutual ties of a randomly selected one percent of her peers - which I name *peers-of-peers*.

I find suggestive evidence of *homophily* in the formation of Twitter's network. Homophily is a tendency to interact with similar individuals - along many dimensions of similarity. In this paper, I find that abortion-rights activists, either pro-choice or pro-life, are highly connected through Twitter - on average, 24% of the users in the peer group are also activists. Nonetheless, the evidence does not support the hypothesis of an *echo-chamber effect*, i.e., the segregation of individuals into like-minded groups, which induces polarization as they interact together. First, for most users, there is no chamber - on average, two-thirds of the activist connections share views on abortion rights, but the remaining one-third are dissidents. Second, there is no echo - the peer effects estimates for like-minded activists do not vary for users with relatively more homogeneous or heterogeneous peer groups.

Following the empirical literature on peer effects, my identification strategy relies on the *partially overlapping network's property*. This property relates to peer groups being individual-specific when social interactions are structured through a network. Bramoullé et al. (2009) and De Giorgi et al. (2010) have shown that this feature helps identify peer effects, as indirect links are a source of valid instrumental variables for peers' actions. Then, I propose a network-based instrumental variable to estimate the parameters. As Twitter data does not provide detailed individual characteristics, I take advantage of the longitudinal structure of the data to include individual fixed effects, which allow me to control unobserved factors driving individuals' actions and network formation.

This paper contributes to the empirical understanding of the social motives of political activism and collective action problems. Cantoni et al. (2019) and Hager et al. (2022) highlight the role of beliefs about others' protest turnout on individual participation, finding strategic substitutability in protest behavior. Enikolopov et al. (2020) show that social image plays a role in the decision to participate in a protest. They also find that online and offline protest participation is positively associated. Closer to my paper, González (2020) finds strategic complementarity in the protest behavior of Chilean students - pointing out a coordination mechanism, and Bursztyn et al. (2021) identify that social interactions are crucial for sustained political engagement. However, their observation of individual networks is approximated by high school and university classmates, respectively. This paper complements the previous studies (i) by providing a precise observation of peers as Twitter links and (ii) by focusing on the intensive rather than the extensive margin of political activism.

This paper also speaks to the empirical literature on peer effects[5] - which are relevant in different scenarios. Nonetheless, the study of heterogeneous peer effects is usually overlooked - where this heterogeneity refers to a differential response of individuals to different types of peers. A relevant exception is the work by Patacchini et al. (2017), who estimate heterogeneous peer effects in education. Relying on the National Longitudinal Survey of Adolescent Health data, they differentiate the peer influence by the tenure of the links and find a persistent peer effect for long-lived links. Consistently with my case study, the source of heterogeneity in the link types relates to the users' viewpoint on abortion rights. Additionally, in this paper, I provide novel evidence on the role of peer effects on social media platforms; in a context where activism is closely related to political rights and social norms.

Lastly, this paper contributes to understanding who - and how individuals - engage in online social interactions, especially in the political sphere.[6] Halberstam and Knight (2016)

[5] See Bramoullé et al. (2020) for a review.
[6] For a review, see Zhuravskaya et al. (2020).

study the type of links that politically engaged users form, finding homophily in their Twitter network. Nonetheless, Gentzkow and Shapiro (2011) reveal that online interactions are less segregated than offline. Conover et al. (2011) show that political retweets are highly segregated along partisan lines, but user mentions are not - as dissidents mention each other frequently. Larson et al. (2019) find that Charlie Hebdo protest participants were more connected to each other through Twitter when compared to users who did not participate. I consider social ties as reciprocal links on Twitter and study a political right without a partisan position in the Argentinian context. Regarding the proportion of like-minded and dissident peers, the data reveals heterogeneity in the peer group composition - pointing out that some users are segregated into like-minded groups, but the majority are not.

The rest of the paper is organized as follows. Sub-section 1.1 introduces the study case. 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 Abortion rights and activism in Argentina

In December 2020, the Argentine Congress legalized abortion on demand. Nevertheless, it was not the first time the Argentine Congress studied that bill. Before that successful attempt, pro-choice activists had put forward the same bill in Congress seven times - from 2005 onward. 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. However, In August 2018, the Senate rejected it by a low margin. 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. Even though abortion rights was a non-partisan topic, most candidates' statements included their individual position. 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. Yet, this is not particular to Argentina but common to many Latin American countries - where abortion access is restrictive.[7] The first evidence of this is the difficulty in passing the law. The sustained mobilization of pro-choice activists and their counter-mobilization by pro-life activists constitutes the second piece of evidence. Pro-choice and pro-life activists organized many public demonstrations over the period. Furthermore, they designed two handkerchiefs to signal their advocacy, which crossed the Argentine borders and became a symbol of abortion rights mobilizations.[8] Crucially, the *online presence* of pro-choice and pro-life activists - the focus of this research - 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.[9]

## 2 Theoretical framework

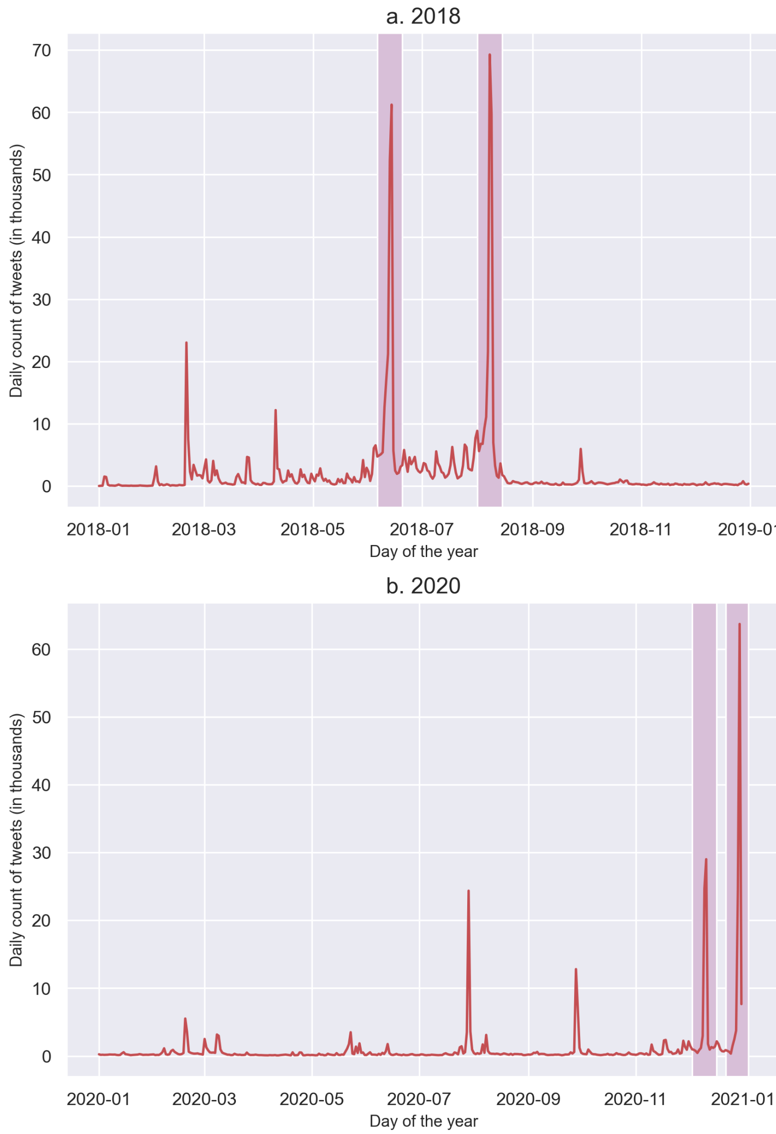
I study a model of social interactions, where individuals choose their level of involvement in *online activism* related to a specific topic $A$ in a *predetermined network*. The links between individuals included in the network represent mutually beneficial relationships. Importantly, individuals care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

[7]Although they have different abortion regulations, most restrict abortion access and only a few allow on-demand abortions. More information is at this link.

[8]Figure 9 in Appendix shows these two bandanas, green for the pro-choice activists and light-blue for pro-life activists. Media pictures of these handkerchiefs are found in abortion rights mobilizations in other Latin American countries and the public demonstrations of Roe vs. Wade in the U.S.

[9]Specifically, 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. Shadow areas indicate weeks of legislative debate on the abortion bill.

## 2.1 A model of peer effects in a network

Consider an online platform comprised of $n < \infty$ individuals, where $N = \{1, ..., n\}$ 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 $g_{ji} \neq 0$ - to capture meaningful online links.[10]

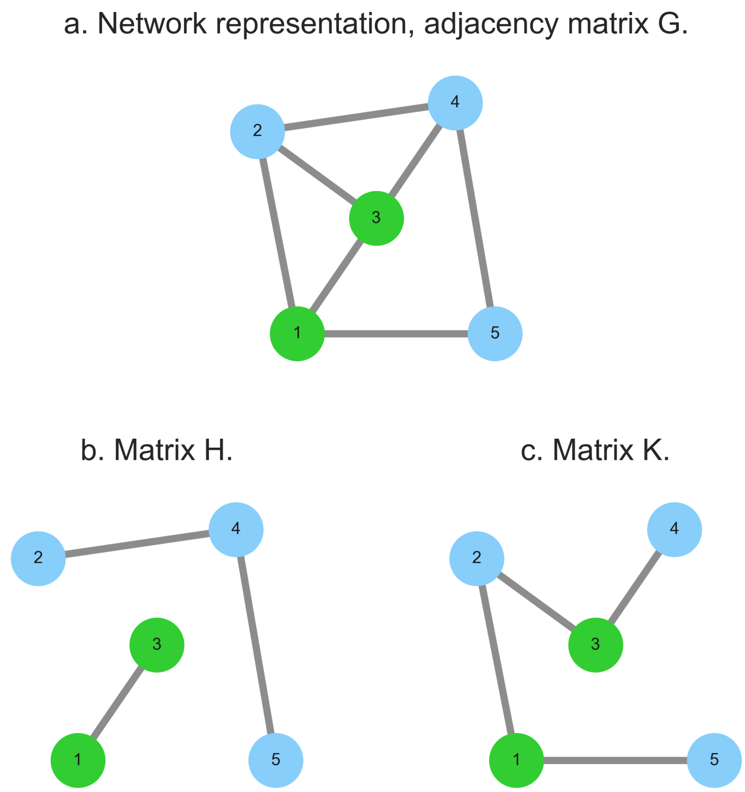
Conditional on the network structure and their preferences, individuals choose online activism, denoted by $a_i \in (-\infty, \infty)$. Importantly, $|a_i|$ denotes the intensity of activism and the sign of $a_i$ indicates whether $i$ is for or against $A$. Each individual $i$ has an ideal point of online activism, denoted $\theta_i \in (-\infty, \infty)$. 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:

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

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, $N = \{1, 2, 3, 4, 5\}$, $\theta_i > 0$ for $i \in \{1, 3\}$ (green nodes), and $\theta_i < 0$ 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.

[10] In the empirical section, I check the sensitivity of the results to this assumption. Section 5 discusses it.

Figure 2: Decomposition of the adjacency matrix $G$




Note: Links between individuals with aligned viewpoints on topic $A$ belong to matrix $H$, whereas links between individuals with opposing viewpoints on topic $A$ belong to 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 $\beta$ reflects peer effects when the sign of own and peers' ideal points coincide, i.e., individuals whose link belongs to matrix $H$. In contrast, $\gamma$ measures peer effects when it differs, i.e., individuals whose link belongs to matrix $K$. Throughout 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:

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

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:

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

Denoting the ideal points vector by $\theta$, the system of best-response functions in matrix notation equals:

$$\mathbf{a} = \theta + \beta H \mathbf{a} + \gamma K \mathbf{a} \tag{3}$$

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:

$$\mathbf{a}(H, K) = [I - \beta H - \gamma K]^{-1}\theta \tag{4}$$

In Appendix A.1, I prove the condition for the invertibility of $[I - \beta H - \gamma K]$ and comment on the 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. Patacchini et al. (2017) also estimates heterogeneous peer effects in education, 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, $\theta_i$, 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 $a_i^* = \theta_i$. Social interactions matter if at least one parameter $(\beta, \gamma)$ is different from zero. A positive value of the equal-sign peers' activism parameter, $\beta$, 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 $\gamma$ 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[11] 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:

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

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). A different approach for network formation would be the one proposed by Goldsmith-Pinkham and Imbens (2013) and Hsieh and Lee (2016). The network formation process is modeled via pairwise stability,[12] while the outcome is specified following equation (4).

[11] See De Paula (2020) for a review of econometric models of network formation.

[12] Jackson and Wolinsky (1996), Calvó-Armengol and Ilkılıç (2009), Jackson and Watts (2001).

# 3 Data

My primary data source is the platform Twitter. I aim to understand how social interactions affect online activism, considering that these interactions could happen between users with aligned or opposing viewpoints in the abortion rights debate. I need to construct a dataset with observable actions and links. In that respect, the first challenge is determining *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 it, 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*. I create a panel dataset with an explicit network structure by combining the tweets' and users' datasets. The following paragraphs explain how I 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.[13] 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 Jackson et al. (2020). The tweets' dataset includes all the replies and quotes to any of those tweets but excludes retweets. I exclude them because of the noise they introduce in classifying pro-choice and pro-life tweets. First, "*retweet* $\neq$ *endorsement*" is widespread on Twitter. Second, retweeting is a Twitter action of low stakes compared to posting or replying to tweets - but their quantitative comparison is not trivial.[14]

I filter tweets according to their content and the account that posted them. The filtering

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

[14] Conover et al. (2011) suggest retweeting is a Twitter action that goes along partisan lines. Thus, if any, by not considering retweets, I am computing a lower bound of online activism.

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 posted by any user, $|a_i|$; and activism sign, stating whether she is a pro-choice or pro-life activist.[15] 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 an integer-valued 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, suppose a tweet includes the hashtag *"#AbortoLegal"* - legal abortion, in Spanish - and *"feminazi"* - the combination of feminist and Nazi. In that case, I classify it 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

[15] A 90% of the initial nodes are pro-choice activists, whereas the 10% remaining is composed of pro-life activists.

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. First, 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 for tractability.[16]

After applying this filtering criterion, the users' dataset contains approximately 6.000 initial nodes. For any initial node, I download a list of her mutual connections, i.e., an account that follows and is followed by 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 percent[17] 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 consistency, I filter accounts with less than 5.000 connections for peers and peers-of-peers. 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.[18] 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 *non-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 *t-posting* or *t-not-posting*, depending whether $a_{it} > 0$ or $a_{it} = 0$. Thus, an non-activist is a user whose activity status equals t-not-posting for all the periods. At the same

[16]Twitter is a giant network, so restricting the number of connections alleviates the computational burden.
[17]For each $i$, I download that list for the closer natural number to $1\% n_i$.
[18]Twitter requests to this endpoint were made between December 2021 and February 2022.

time, an activist is any user whose activity status equals t-posting at least for some $t$. Thus, the categorization of peers into activist or non-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 and early activists. On average, individuals have 412 reciprocal links, of which 97 are activists. Moreover, the set of activists who were t-posting 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 nodes have 38 t-posting peers. Combined with the full observability of Twitter links, small peer groups make this context ideal for studying peer effects.

Table 1: Initial nodes' degree

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

Note: $n_i$ denotes the size of the peer group, whereas $n_i^a$ and $n_i^{ea}$ is the size of the peer group classified as activists and early activists, respectively. mean $n_{it}^a$ is the mean size, across time, of activists' peers who were t-posting 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 illustrates it for equal-sign peers' activism, whereas Panel B is for opposite-sign peers' activism.

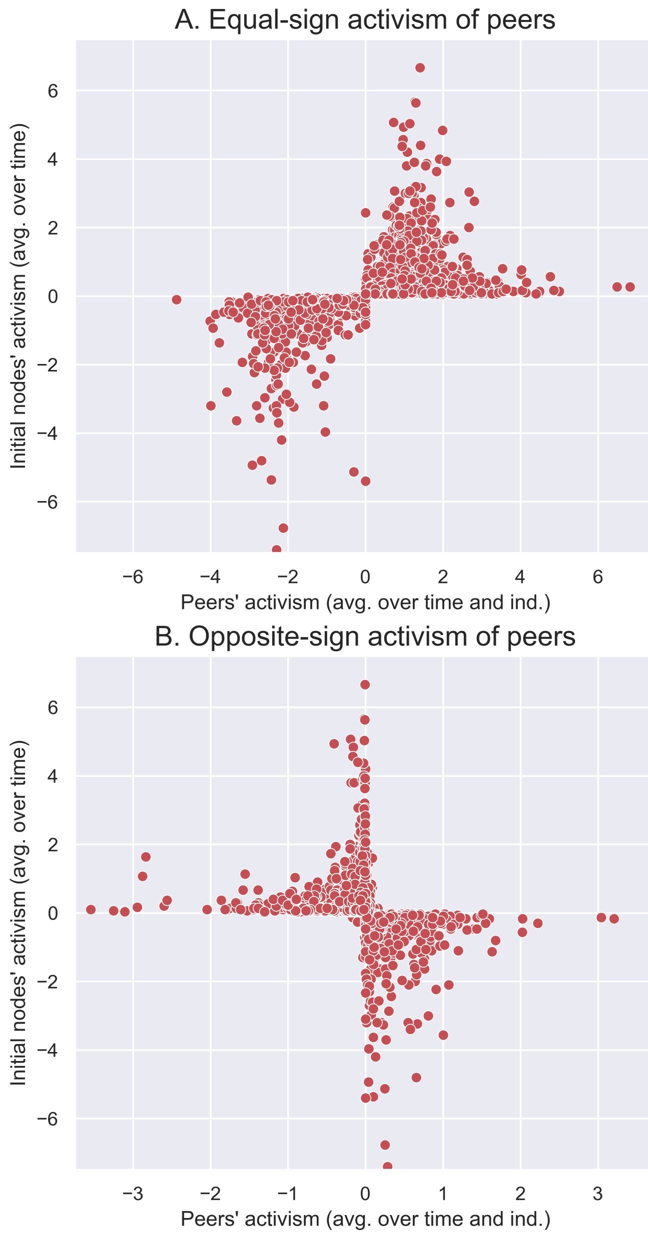
While the correlation between equal-sign peers' and own activism is positive, its analogous statistic for opposite-sign activism is negative. Since the intensity of activism is its absolute value, the sign of the two correlations reflects a positive relationship between activism intensities. The intensity 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.

In the two panels, points where activism of initial nodes is close to, but not equal to, zero reflect that the user was t-not-posting 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 t-posting 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.[19] 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 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.

[19] 1636 out of the 5808 users.

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




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 t-posting 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 t-posting 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.

Table 2: Descriptive statistics

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

Note: Panel A and B variables in this table are averaged over time and individuals, whereas Panel C variables are averaged over individuals. The activists' peers ratio is the proportion of activists in the peer group. The early activists' peers ratio is the proportion of early activists among activists' peers.

According to Panel C, 24% of users in the peer groups are activists, on average.[20] 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

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

literature studying the existence of online echo chambers is inconclusive,[21] there is evidence that activists are highly connected through social media, e.g., Larson et al. (2019). Accordingly, the description of this context is consistent with *homophily* in Twitter's network, in the sense of being engaged in the abortion rights debate 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. 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.


[21]See Levy and Razin (2019) for a review of echo chambers.

# 4 Empirical analysis

In this section, I follow an instrumental variables approach to estimate the heterogeneous peer effect parameters. Consistently with section 2, I estimate peer effects by contemplating links between like-minded users and users with opposing 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 characteristics[22] 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* is the impact of peers' actions on an individual's actions. Lastly, individuals and their peers may behave similarly due to sharing a common environment, the so-called *correlated effect*. Therefore, the causal estimation of endogenous peer effects requires disentangling them from contextual and

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

correlated effects. This distinction becomes easier when interactions are structured through a network.

When a network structures social interactions, the peer group of any individual is *specific* to her. This feature alleviates Manski's *reflection problem*, making the distinction between endogenous and exogenous effects possible. Specifically, the reflection problem is a consequence of the simultaneity in the behavior of individuals, see equation (3), and it arises only under the assumption of group-wise interactions.[23] Even though I do not estimate exogenous effects and, instead, I control for them by using individual fixed effects, network data is still crucial for the identification strategy. The reason is the (potential) existence of correlated effects, that is, group-specific unobserved variables driving individual's and peers' actions. Since peer groups are individual-specific, the characteristics of indirect links in the network are valid instrumental variables for peers' actions.[24]

In this paper, I follow a network-based instrumental variable approach to causally estimate peer effects.[25] 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. An intransitive triad between individuals $(i, j, l)$ exists if, for the pair of individuals $(i, j)$, there exists an individual $l$ 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. As I estimate heterogeneous peer effects, I split this set and the peer group $P_i$ into two subsets each: $(P_i^H, P_{j/i}^H)$, containing information about equal-sign

[23]That is, when individuals are affected by all individuals belonging to their group and by nobody outside them.
[24]The indirect links of any individual share a common environment with the individual's peers but not with her.
[25]In the context of Twitter, Cagé et al. (2022) also use a network-based instrument to study the information propagation from social media to mainstream media.

activism, and $(P_i^K, P_{j/i}^K)$, about opposite-sign activism. The proposed instrumental variables are the *daily ratios of equal-sign and opposite-sign t-posting users* among those in $(P_{j/i}^H; P_{j/i}^K)$. 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 t-posting 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 t-posting 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 initial node, $l \notin P_i$, only affects her activism, $a_i$, through the activism of peers, $j \in P_i$.

An additional concern in the estimation of peer effects is the *exclusion bias*, a downward bias in the OLS estimates of peer effects, e.g., Caeyers and Fafchamps (2016), and Angrist (2014). To address it, I follow the former article, and I include the instrument's value for the initial nodes as an additional control in the IV estimation. For any initial node $i$ and day $t$, the parametric specification of the individual heterogeneity $\theta_{it}$ and the resulting empirical counterpart of equation (2) are:

$$\theta_{it} = \theta_x x_{it} + \theta_{LD} + \theta_i + \epsilon_{it}$$

$$a_{it} = \theta_x x_{it} + \beta \sum_{j \in P_i^H} a_{jt} + \gamma \sum_{j \in P_i^K} a_{jt} + \theta_{LD} + \theta_i + \epsilon_{it}$$

where $x_{it}$ is a set of covariates related to the tweet's popularity, i.e., the daily average of likes, retweets, quotes, and replies to the user's tweets. $\theta_i$ is an individual fixed effect. $\theta_{LD}$ is a dummy variable that takes value one when Congress debated the abortion rights bill, i.e., on a legislative day, and zero otherwise. $\epsilon_{it}$ is and *i.i.d.* error term with variance $\sigma^2$.

The reason I include individual fixed effects is twofold. First, to control for unobserved factors driving Twitter users' behavior and, among them, potential contextual effects. Additionally, individual fixed effects control for 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. Nonetheless, individual fixed effects are crucial, given the Twitter data characteristics. Working with this data has the advantage of clear observability of links but at the cost of lacking detailed individual characteristics. These characteristics constitute the source of identifying exogenous peer effects and determine the sorting of individuals into a network.

In the context of social media, a potential threat to identification is given by how the *Twitter algorithm* works. In particular, regarding the content shown in the Twitter feed of any user whose author is not her peer. Although there is no official information about the algorithm, it is reasonable to assume the observation of such content is more likely to happen if the tweet becomes viral or if the tweet's author and the user share connections. Regarding the former, I include tweet popularity measures in the estimation. Finally, the essence of an instrumental variable is that the instrument and the independent variable are related only via the endogenous variable. In the Twitter context, it translates to the user and the tweet's author being related through their peers in common.

## 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 variable approach (IV-FE). Panel A includes all the observations for one-week windows centered on the legislative days,[26] 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.

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

Coefficients of equal-sign activism levels are positive and significant. For instance, IV-FE estimates in Column (4) indicate that a 1-tweet increment on the equal-sign activism of peers increases initial nodes' activism by 0.49 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 0.42 tweets, according to Column (4).

Table 3: Peer effects in online activism.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: Balanced Panel | | | | |
| $\text{activism}_{\text{equal-sign}}$ | 0.194*** | 0.134*** | 0.728*** | 0.494*** |
| | (0.014) | (0.011) | (0.049) | (0.047) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.181*** | -0.178*** | -0.083 | -0.423** |
| | (0.044) | (0.044) | (0.152) | (0.136) |
| Kleibergen-Paap rk LM stat. | | | 174.736 | 191.624 |
| Obs. | 174238 | 174238 | 174238 | 174238 |
| Panel B: Unbalanced Panel | | | | |
| $\text{activism}_{\text{equal-sign}}$ | 0.350*** | 0.289*** | 1.177*** | 0.991*** |
| | (0.038) | (0.037) | (0.160) | (0.195) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.376* | -0.388* | -0.489 | -0.737** |
| | (0.157) | (0.159) | (0.257) | (0.278) |
| Kleibergen-Paap rk LM stat. | | | 154.82 | 107.896 |
| Obs. | 27652 | 27652 | 27652 | 27652 |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |
| Ind. | 5808 | 5808 | 5808 | 5808 |

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. * p<.05, ** p<.01, *** p<.001.

The comparison between FE and IV-FE estimates suggests that complementarities in online activism are more substantial for the IV estimates. The difference in their magnitude is in line with the fact that these estimators compute different average treatment effects (ATE).[27] Additionally, this difference could be explained by the OLS exclusion bias and the characteristics of the compliers. Importantly, the sign and statistical 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 online activism includes days in which Twitter users were t-not-posting.

### 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, 45%, and of zero otherwise.

The results suggest that the strategic complementarity between equal-sign activist peers increases as their exposure to early activism. Coefficients of the interaction between equal-sign activism and exposure are positive and significant across all specifications except Column (3). 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. 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

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

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: Exposure to early activism.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{activism}_{\text{equal-sign}}$ | 0.153*** | 0.102*** | 0.689*** | 0.423*** |
| | (0.016) | (0.013) | (0.052) | (0.052) |
| $\text{exposure} * \text{activism}_{\text{equal-sign}}$ | 0.078** | 0.063** | 0.067 | 0.116** |
| | (0.027) | (0.021) | (0.041) | (0.039) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.144*** | -0.133*** | -0.042 | -0.406** |
| | (0.032) | (0.031) | (0.156) | (0.146) |
| $\text{exposure} * \text{activism}_{\text{opposite-sign}}$ | -0.070 | -0.085 | -0.116 | -0.105 |
| | (0.085) | (0.086) | (0.286) | (0.260) |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |
| Kleibergen-Paap rk LM stat. | | | 107.985 | 127.798 |
| Ind. | 5808 | 5808 | 5808 | 5808 |
| Obs. | 174238 | 174238 | 174238 | 174238 |

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 activist-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. * $p<.05$, ** $p<.01$, *** $p<.001$.

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.

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 results[28] 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.

Table 5: Homogeneous and heterogeneous peer groups.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{activism}_{\text{equal-sign}}$ | 0.231*** | 0.175*** | 0.727*** | 0.482*** |
| | (0.017) | (0.015) | (0.051) | (0.050) |
| $\text{homog} * \text{activism}_{\text{equal-sign}}$ | -0.076** | -0.081*** | 0.017 | 0.040 |
| | (0.025) | (0.019) | (0.044) | (0.041) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.165*** | -0.162*** | 0.019 | -0.360** |
| | (0.042) | (0.043) | (0.127) | (0.121) |
| $\text{homog} * \text{activism}_{\text{opposite-sign}}$ | -1.216*** | -0.984*** | -2.709 | -2.104 |
| | (0.177) | (0.155) | (2.297) | (1.952) |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |
| Kleibergen-Paap rk LM stat. | | | 20.900 | 21.303 |
| Ind. | 5808 | 5808 | 5808 | 5808 |
| Obs. | 174238 | 174238 | 174238 | 174238 |

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. * p<.05, ** p<.01, *** p<.001.

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., 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

[28]This 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.

insignificant for the IV specifications.

## 5 Robustness checks

In this section, I check the robustness of my results by relaxing the assumptions I made throughout the paper. Appendix A.3 presents the corresponding results.

**Unilateral links** In sections 2 and 4, I assume that links are undirected, i.e, $g_{ij} \neq 0$ if and only if $g_{ji} \neq 0$. Now, I check the sensitivity of the results to such an assumption. I perform the analysis for undirected networks - considering the peers of each initial node as the set of users who have a unilateral link with her. First, I analyze *Twitter's friends* - users followed by the initial node. Later, I consider *Twitter's followers* - users following the initial node. As seen in Appendix A.3, the results remain qualitatively unchanged when considering followers as the peer group. It is true for both FE and IV-FE regressions.

Nevertheless, the results are mixed when the peer group is the set of accounts followed by the initial node - Twitter's friends. These results vary for peers with aligned and opposing viewpoints on abortion rights. In the case of like-minded peers, the results are analogous, in sign and statistical significance, to the ones presented in section 4, and only slightly higher in magnitude. The estimates of opposite-sign activism of peers decrease in magnitude for the FE model. The estimates become non-statistically significant or even change their sign in the IV regressions.

**Time span** Next, I expand the period considered in the empirical analysis. I do so to see whether the results change when the abortion rights debate becomes less salient. Specifically, I utilize the dataset with observations for a two-weeks window centered on each day Congress debated the abortion rights bill instead of one-week periods. Tables in Appendix A.3 show that the results of section 4 are robust to the extension of the time span.

# 6 Conclusion

As social media platforms have proliferated, a new public sphere where individuals connect and share ideas has emerged. Understanding how individuals engage in online interactions and how these interactions impact political outcomes is crucial for modern economies. In that regard, this paper provides novel evidence of the role of peer effects on political activism through social media platforms.

The estimates of peer effects in Section 4 indicate that activism exhibits strong complementarities. Remarkably, activist peers with aligned or opposing viewpoints on abortion rights have a similar effect in terms of magnitude. As mentioned, these results correspond to peer effects on the intensive margin of political activism. A natural extension of this project would also analyze the decision to be a social media activist - which posits an empirical challenge regarding its identification strategy. It will then be possible to determine whether extensive and intensive margins of activism exhibit similar patterns.

In addition, this paper suggests that the peer group's composition plays a role in understanding individual behavior - for instance, regarding exposure to early activism or the proportion of like-minded and dissident activists in the peer group. As such, social media platforms present an ideal context for further research on the influence of peers on individual behavior, as they provide detailed and precise information about social ties and online interactions. Related to this paper, some of these questions are how collective claims are created, by whom, how they evolve, and whether they persist.

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# A Appendix

## A.1 A model of peer effects in a network

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 (4). The proof consists of two steps. First, demonstrate that provided $|\beta| < 1$ and $|\gamma| < 1$, the matrix $[I - \beta H - \gamma K]$ is a *strictly diagonally dominant* matrix. Then, apply the *Gershgorin's circle theorem* to argue that the matrix is non-singular and, consequently, that its inverse exists.

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. Then, it follows that $[I - \beta H - \gamma K]$ is strictly diagonally dominant, and that $[I - \beta H - \gamma K]^{-1}$ exists.

As the inverse is unique, a unique vector $\mathbf{a}$ is compatible with equation (4).

## A.2 Data

### A.2.1 Twitter data collection

Twitter is an online platform that allows users to publish short messages, of a maximum of 140 characters, on their profiles. 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.2.2 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 activist-peers ratio.

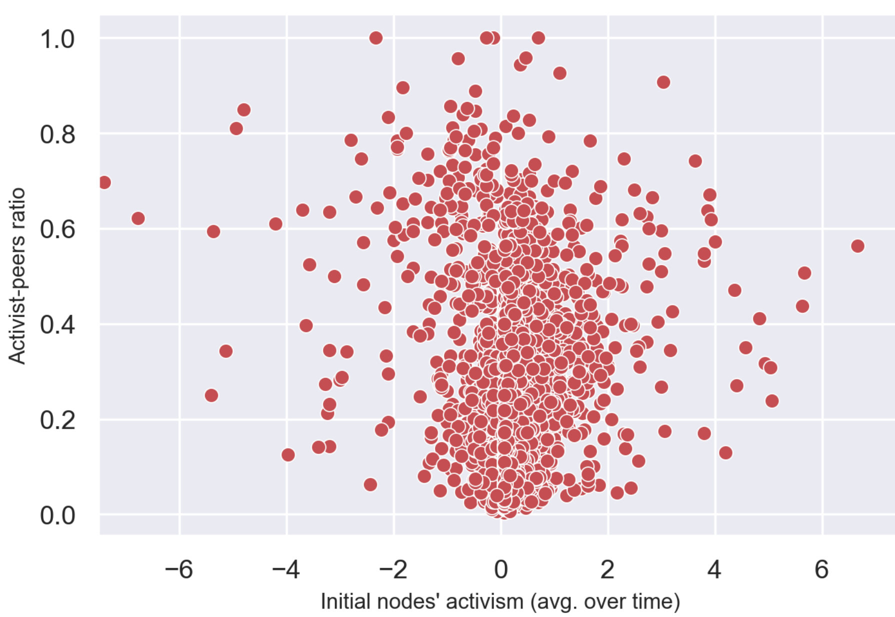


Figure 6: Histograms of average activism levels of initial nodes and their connections.

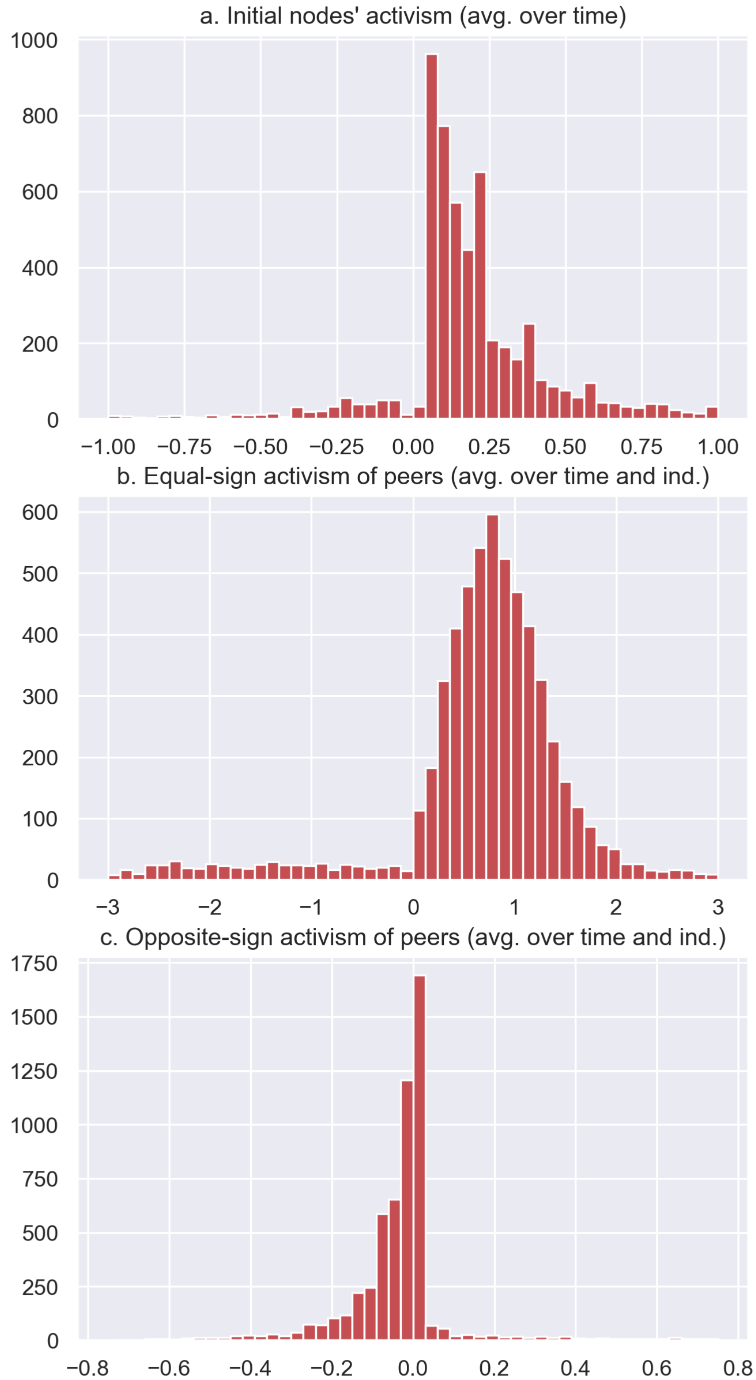


Figure 7: Histograms of activist connections (avg. over time). Pro-choice initial nodes.

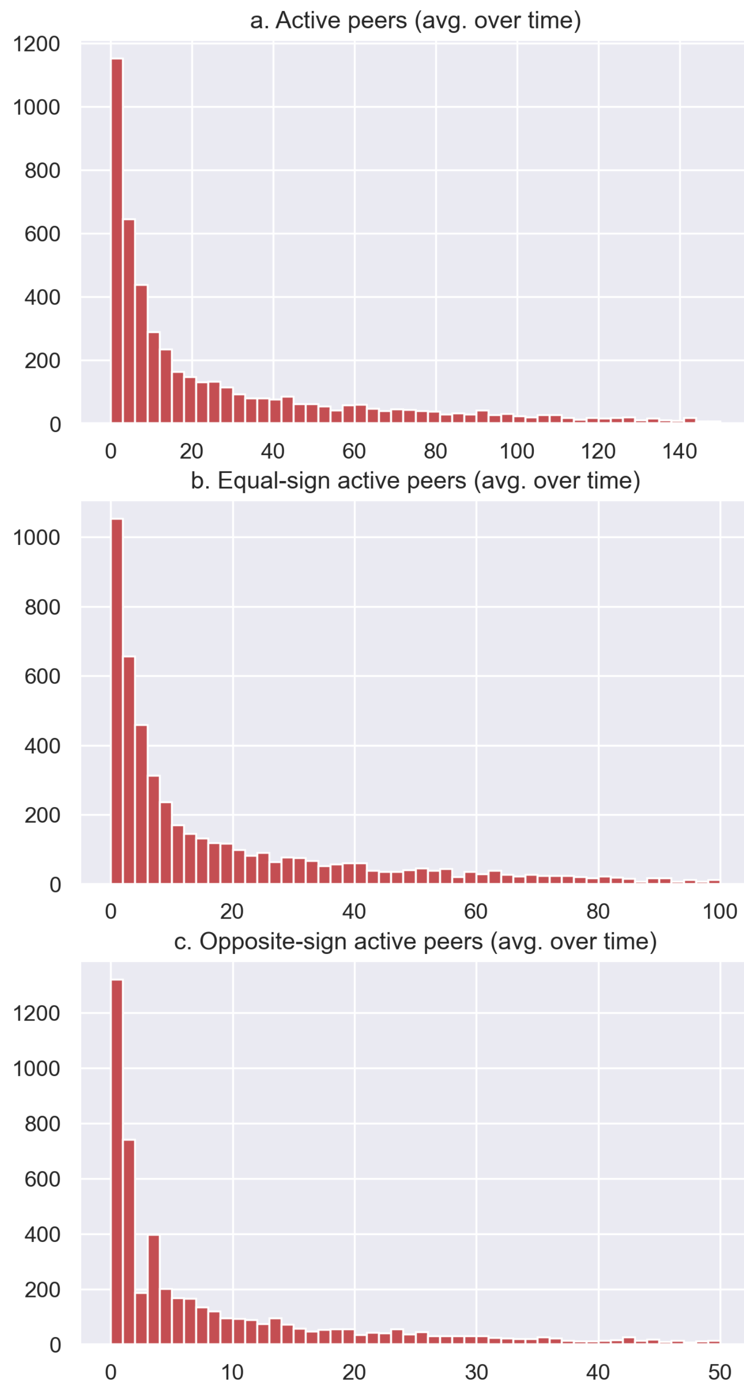
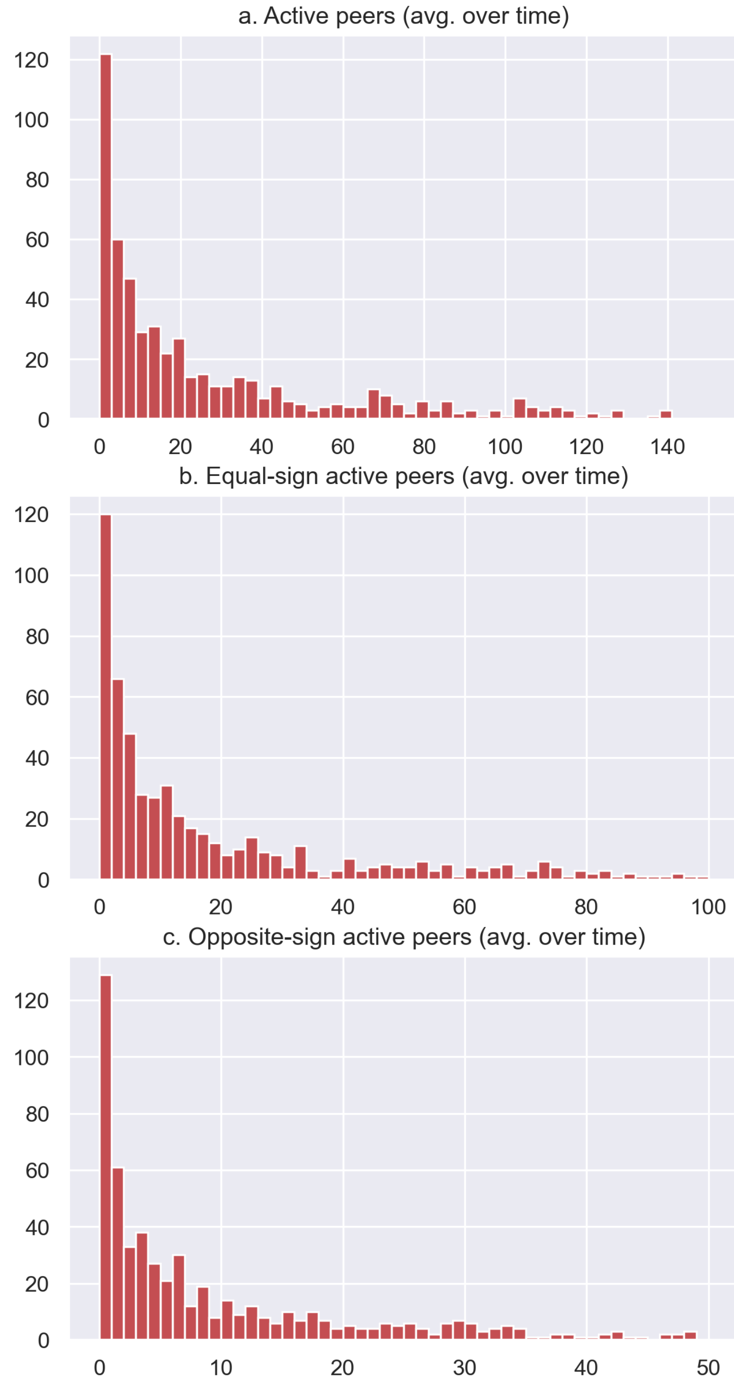


Figure 8: Histograms of activist connections (avg. over time). Pro-life initial nodes.



## A.3 Empirical analysis

### A.3.1 Increasing the time span

Table 7: Peer effects in online activism. Two-weeks period.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: Balanced Panel | | | | |
| $\text{activism}_{\text{equal-sign}}$ | 0.192*** | 0.138*** | 0.657*** | 0.468*** |
| | (0.011) | (0.010) | (0.039) | (0.039) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.165*** | -0.161*** | -0.234* | -0.461*** |
| | (0.025) | (0.025) | (0.105) | (0.099) |
| Kleibergen-Paap rk LM stat. | | | 232.652 | 250.165 |
| Obs. | 354345 | 354345 | 354345 | 354345 |
| Panel B: Unbalanced Panel | | | | |
| $\text{activism}_{\text{equal-sign}}$ | 0.408*** | 0.350*** | 1.030*** | 0.875*** |
| | (0.041) | (0.041) | (0.117) | (0.136) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.301** | -0.314** | -0.672** | -0.911*** |
| | (0.095) | (0.098) | (0.207) | (0.221) |
| Kleibergen-Paap rk LM stat. | | | 207.144 | 187.592 |
| Obs. | 33597 | 33597 | 33597 | 33597 |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |
| Ind. | 5809 | 5809 | 5809 | 5809 |

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for two-weeks 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. * p<.05, ** p<.01, *** p<.001.

Table 8: Exposure to early activism. Two-weeks period.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{activism}_{\text{equal-sign}}$ | 0.155*** | 0.107*** | 0.614*** | 0.395*** |
| | (0.013) | (0.011) | (0.044) | (0.044) |
| $\text{exposure} * \text{activism}_{\text{equal-sign}}$ | 0.071*** | 0.059*** | 0.078* | 0.119*** |
| | (0.021) | (0.017) | (0.034) | (0.033) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.159*** | -0.147*** | -0.193 | -0.449*** |
| | (0.031) | (0.030) | (0.128) | (0.120) |
| $\text{exposure} * \text{activism}_{\text{opposite-sign}}$ | -0.013 | -0.027 | -0.122 | -0.102 |
| | (0.050) | (0.050) | (0.197) | (0.185) |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |
| Kleibergen-Paap rk LM stat. | | | 116.930 | 126.320 |
| Ind. | 5809 | 5809 | 5809 | 5809 |
| Obs. | 354345 | 354345 | 354345 | 354345 |

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for two-weeks periods centered on legislative days. Exposure is a dummy variable that takes a value of 1 if the early activist-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. * p<.05, ** p<.01, *** p<.001.

Table 9: Homogeneous and heterogeneous peer groups. Two-weeks period.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{activism}_{\text{equal-sign}}$ | 0.198*** | 0.157*** | 0.633*** | 0.426*** |
| | (0.014) | (0.013) | (0.048) | (0.047) |
| $\text{homog} * \text{activism}_{\text{equal-sign}}$ | -0.014 | -0.039* | 0.07 | 0.094** |
| | (0.021) | (0.017) | (0.037) | (0.035) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.151*** | -0.144*** | -0.065 | -0.360*** |
| | (0.024) | (0.023) | (0.110) | (0.105) |
| $\text{homog} * \text{activism}_{\text{opposite-sign}}$ | -0.918*** | -0.746*** | -2.035** | -1.568** |
| | (0.097) | (0.091) | (0.641) | (0.580) |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |
| Kleibergen-Paap rk LM stat. | | | 188.471 | 212.626 |
| Ind. | 5809 | 5809 | 5809 | 5809 |
| Obs. | 354345 | 354345 | 354345 | 354345 |

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for two-weeks 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. * p<.05, ** p<.01, *** p<.001.

### A.3.2 Considering unilateral links

Table 10: Peer effects in online activism. Friends as peers.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: Balanced Panel | | | | |
| activism$_{\text{equal-sign}}$ | 0.152*** | 0.101*** | 1.010*** | 0.614*** |
| | (0.006) | (0.006) | (0.126) | (0.084) |
| activism$_{\text{opposite-sign}}$ | -0.094*** | -0.076*** | 0.316* | -0.141 |
| | (0.011) | (0.011) | (0.152) | (0.102) |
| Kleibergen-Paap rk LM stat. | | | 70.017 | 117.167 |
| Obs. | 173998 | 173998 | 173998 | 173998 |
| Panel B: Unbalanced Panel | | | | |
| activism$_{\text{equal-sign}}$ | 0.337*** | 0.284*** | 1.595*** | 1.312*** |
| | (0.027) | (0.027) | (0.395) | (0.328) |
| activism$_{\text{opposite-sign}}$ | -0.134*** | -0.122*** | 0.255 | -0.013 |
| | (0.024) | (0.025) | (0.356) | (0.288) |
| Kleibergen-Paap rk LM stat. | | | 23.456 | 31.865 |
| Obs. | 27607 | 27607 | 27607 | 27607 |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |
| Ind. | 5800 | 5800 | 5800 | 5800 |

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. The peer group is the set of Twitter accounts followed by the individual. 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. * p<.05, ** p<.01, *** p<.001.

Table 11: Peer effects in online activism. Followers as peers.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: Balanced Panel | | | | |
| activism$_{\text{equal-sign}}$ | 0.211*** | 0.148*** | 0.754*** | 0.508*** |
| | (0.014) | (0.012) | (0.062) | (0.056) |
| activism$_{\text{opposite-sign}}$ | -0.115*** | -0.103*** | -0.016 | -0.346** |
| | (0.017) | (0.016) | (0.133) | (0.118) |
| Kleibergen-Paap rk LM stat. | | | 152.561 | 176.463 |
| Obs. | 174119 | 174119 | 174119 | 174119 |
| Panel B: Unbalanced Panel | | | | |
| activism$_{\text{equal-sign}}$ | 0.412*** | 0.342*** | 1.185*** | 1.018*** |
| | (0.038) | (0.038) | (0.196) | (0.231) |
| activism$_{\text{opposite-sign}}$ | -0.172*** | -0.176*** | -0.483* | -0.683** |
| | (0.052) | (0.053) | (0.234) | (0.250) |
| Kleibergen-Paap rk LM stat. | | | 103.118 | 79.092 |
| Obs. | 27632 | 27632 | 27632 | 27632 |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |
| Ind. | 5804 | 5804 | 5804 | 5804 |

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. The peer group is the set of Twitter accounts that follow the individual. 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. * p<.05, ** p<.01, *** p<.001.

Table 12: Exposure to early activism. Unilateral links.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: Friends as peers | | | | |
| $\text{activism}_{\text{equal-sign}}$ | 0.086*** | 0.057*** | 0.973*** | 0.567*** |
| | (0.009) | (0.008) | (0.118) | (0.084) |
| $\text{exposure} * \text{activism}_{\text{equal-sign}}$ | 0.089*** | 0.060*** | 0.042 | 0.056 |
| | (0.012) | (0.010) | (0.068) | (0.058) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.148*** | -0.138*** | 0.395 | -0.128 |
| | (0.027) | (0.026) | (0.226) | (0.175) |
| $\text{exposure} * \text{activism}_{\text{opposite-sign}}$ | 0.063* | 0.070* | -0.11 | -0.031 |
| | (0.029) | (0.028) | (0.256) | (0.210) |
| Kleibergen-Paap rk LM stat. | | | 66.424 | 110.842 |
| Ind. | 5800 | 5800 | 5800 | 5800 |
| Obs. | 173998 | 173998 | 173998 | 173998 |
| Panel B: Followers as peers | | | | |
| $\text{activism}_{\text{equal-sign}}$ | 0.177*** | 0.124*** | 0.740*** | 0.481*** |
| | (0.016) | (0.013) | (0.066) | (0.059) |
| $\text{exposure} * \text{activism}_{\text{equal-sign}}$ | 0.081** | 0.058* | 0.032 | 0.058 |
| | (0.029) | (0.022) | (0.047) | (0.044) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.125*** | -0.110*** | -0.004 | -0.327** |
| | (0.023) | (0.021) | (0.147) | (0.123) |
| $\text{exposure} * \text{activism}_{\text{opposite-sign}}$ | 0.025 | 0.017 | -0.034 | -0.061 |
| | (0.035) | (0.032) | (0.258) | (0.243) |
| Kleibergen-Paap rk LM stat. | | | 102.380 | 108.040 |
| Ind. | 5804 | 5804 | 5804 | 5804 |
| Obs. | 174119 | 174119 | 174119 | 174119 |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset. Daily observations for one-week periods centered on legislative days. Panel A: The peer group is the set of Twitter accounts followed by the individual. Panel B: The peer group is the set of Twitter accounts that follow the individual. Exposure is a dummy variable that takes a value of 1 if the early activist-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. * p<.05, ** p<.01, *** p<.001.

Table 13: Homogeneous and heterogeneous peer groups. Unilateral links.

| | FE | | IV-FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Panel A: Friends as peers | | | | |
| $\text{activism}_{\text{equal-sign}}$ | 0.163*** | 0.113*** | 1.072*** | 0.631*** |
| | (0.007) | (0.007) | (0.143) | (0.089) |
| $\text{homog} * \text{activism}_{\text{equal-sign}}$ | -0.052*** | -0.054*** | -0.146* | -0.022 |
| | (0.014) | (0.011) | (0.058) | (0.044) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.090*** | -0.071*** | 0.439* | -0.099 |
| | (0.011) | (0.011) | (0.178) | (0.111) |
| $\text{homog} * \text{activism}_{\text{opposite-sign}}$ | -0.694*** | -0.696*** | -1.584 | -0.828 |
| | (0.117) | (0.103) | (0.913) | (0.750) |
| Kleibergen-Paap rk LM stat. | | | 55.660 | 99.383 |
| Ind. | 5800 | 5800 | 5800 | 5800 |
| Obs. | 173998 | 173998 | 173998 | 173998 |
| Panel B: Followers as peers | | | | |
| $\text{activism}_{\text{equal-sign}}$ | 0.222*** | 0.164*** | 0.748*** | 0.494*** |
| | (0.018) | (0.015) | (0.064) | (0.058) |
| $\text{homog} * \text{activism}_{\text{equal-sign}}$ | (0.038) | -0.057** | 0.036 | 0.065 |
| | (0.027) | (0.020) | (0.048) | (0.045) |
| $\text{activism}_{\text{opposite-sign}}$ | -0.109*** | -0.096*** | -0.014 | -0.355** |
| | (0.017) | (0.016) | (0.134) | (0.118) |
| $\text{homog} * \text{activism}_{\text{opposite-sign}}$ | -0.992*** | -0.838*** | -0.266 | -0.217 |
| | (0.148) | (0.126) | (1.312) | (1.215) |
| Kleibergen-Paap rk LM stat. | | | 137.605 | 163.684 |
| Ind. | 5804 | 5804 | 5804 | 5804 |
| Obs. | 174119 | 174119 | 174119 | 174119 |
| Controls | No | Yes | No | Yes |
| LegDays FE | No | Yes | No | Yes |

Note: Standard errors clustered by individuals in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. Panel A: The peer group is the set of Twitter accounts followed by the individual. Panel B: The peer group is the set of Twitter accounts that follow the individual. 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. * p<.05, ** p<.01, *** p<.001.

## A.4 Abortion rights and activism in Argentina

Figure 9 shows the handkerchiefs designed by the Argentinian pro-choice and pro-life activists, respectively.

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