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

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Preliminary and incomplete

Abstract

This paper studies peer effects on online activism in the context of Argentina's abortion-rights debate. Pro-choice and pro-life movements coexisted. Theoretically, I develop a model of strategic interactions in a predetermined but endogenous network. The model allows for a differential of peers among participants on equal or opposite movements. Empirically, I estimate peer effects and test if actions are strategic substitutes or complements. Through the combination of tweets and Twitter users' data, I create a novel panel dataset with an explicit network structure. I provide a reduced-form analysis following an Instrumental Variables approach. Additionally, I estimate the model by Maximum Likelihood, controlling for network endogeneity. Results indicate the existence of solid complementarities in activism levels and homophily in network formation.

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

JEL Codes: D74, D85, P00, Z13

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1 Introduction

Do social interactions[1] affect individual activism? How does *our political behaviour* relate to *our friends' political behaviour*? Is activism an action of strategic substitutability or complementarity? In a novel setting, this paper attempts to answer these questions.

Particularly, I analyze publicly-observed posts on Twitter associated with a controversial, perhaps normative, topic. Because of the nature of the topic, as well as heterogeneity in preferences and the observability of actions, social interactions are crucial to determining individual activism.

Culture, social norms, religion, and policy include some of the most controversial and normative topics. This study focuses on a specific issue, Argentina's abortion-rights debate. Congress discussed a bill to legalize abortion on demand in 2018 and 2020. During the debate, citizens could express their opinion about it if they wish so. Pro-choice and pro-life campaigns coexisted and were actively seeking participants. Notably, the online presence of the abortion-rights debate was vigorous.

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 movement. It is agnostic about the existence of strategic substitutability or complementarity in actions to be suitable for empirically testing it.

In the data analysis, I combine tweets and users' information to generate a *panel dataset* with an explicit *network structure*. For any Twitter user in the dataset, I observe (i) the set of her reciprocal links and (ii) the abortion-related tweets she and her connections posted. The novel structure of the dataset and the precise observation of links on Twitter make this setting ideal for estimating peer effects.

Empirically, I provide a reduced-form analysis and a Maximum Likelihood Estimation based on the theoretical model. For the reduced-form estimates of peer effects, I follow an Instrumental Variables approach. I take *peers of peers' actions* as an instrument for

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

peers' actions. Based on the Twitter algorithm, which determines the probability of observing a tweet in the feed, I weigh the proposed instrument. This weight depends on the number of links of the reader and author of the tweet, as well as the tweet's popularity.

Additionally, I provide a Maximum Likelihood Estimation, 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 measure of text similarity. I employ a Short Text Topic Modeling Technique (STTMT) proposed by Yin and Wang (2014).

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, the presence of strategic complementarities in activism is not as frequent. This paper, in this regard, contributes to the literature on peer effects not only through its methodological approach and novelty of the dataset but also through its results.

The rest of the paper is organized as follows. Subsection 1.2 introduces the context of the Argentinian abortion-rights debate. Section 2 presents the model, and Section 3 describes the data. Sections 4 and 5 present the reduced-form and structural estimates of peer effects, 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)

Activism, polarization, and protest participation (González, 2020) (Bursztyn et al., 2021) (Hager et al., 2022) (Halberstam and Knight, 2016) (Enikolopov et al., 2020) (Bursztyn et al., 2020)

DCM with social interactions (Brock and Durlauf, 2001) (Brock and Durlauf, 2003) (Bayer and Timmins, 2007) (Blume et al., 2011)

Social networks - theory (Ballester et al., 2006) (Jackson and Wolinsky, 1996) (Genicot, 2022)

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.

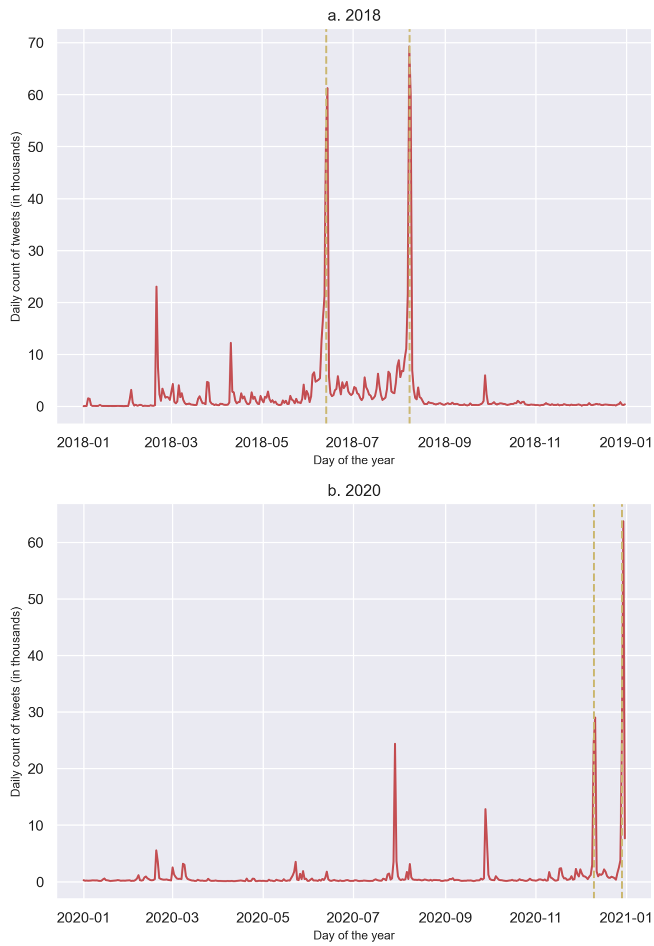
Both cameras finally approved the law, as mentioned before, in December 2020. The previous year, 2019, was an electoral year in Argentina. As a result of the national elections, one-third of the seats in Congress changed. Most of the candidate's statements included the candidate's position on abortion rights. Moreover, Congress members did not change their vote on the bill between 2018 and 2020. 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 for this is the difficulty in passing the law. Yet, this is not particular to Argentina but common to many Latin American countries. Although

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

they have different abortion regulations, most restrict abortion access. Only a few allow on-demand abortions.

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.

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 two handkerchiefs, green and light-blue, to signal their advocacy. The usage of the pro-choice handkerchief crossed the Argentine borders. This green bandana became an international symbol of abortion-rights mobilizations.

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

2 Theoretical framework

I study a model of social interaction, 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 level of individuals with whom they interact.

Activism level of a given individual is characterized by its *intensity* and *direction*. Activism intensity relates to the individual effort in devoting time to being an activist. Activism direction 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. Let G be an $n \times n$ matrix representing the online friendship of those individuals. The (i, j) entry of G, denoted g_{ij}, equals one 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 is symmetric.

Conditional on the network structure, individuals choose their online activism level on the 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.

Following the literature, I assume a linear quadratic specification for the utility of activism levels. Denoting any profile of activism levels by $\mathbf{a}$, the following function represents i's utility:

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

$$u_i(\mathbf{a}, G) = \alpha_i a_i - \frac{1}{2}a_i^2 + \beta\frac{1}{n_i}\sum_{j\in N} g_{ij}\mathbb{1}_{\alpha_i\times\alpha_j>0}a_i a_j + \gamma\frac{1}{n_i}\sum_{j\in N} g_{ij}\mathbb{1}_{\alpha_i\times\alpha_j<0}a_i a_j \qquad (1)$$

where $\alpha_i \in (-\infty, \infty)$ represents individual heterogeneity. 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 social benefit or cost of changing an individual's action. Importantly, the model allows for a differential effect of peers depending on activism signs. The parameter β reflects peer effects when the sign of own and peers' idiosyncratic term coincide, while γ measures peer effects when it differs.

Individuals play a non-cooperative game for the choice of the activism levels, conditional on the network structure. The equilibrium concept is Nash equilibrium. The existence and uniqueness of the equilibrium for a fixed network structure follow directly from the literature, e.g., (Ballester et al., 2006). For any individual i, the Best Response function is given by:

$$a_i^{BR} = \alpha_i + \beta\frac{1}{n_i}\sum_{j\in N} g_{ij}\mathbb{1}_{\alpha_i\times\alpha_j>0}a_j^{BR} + \gamma\frac{1}{n_i}\sum_{j\in N} g_{ij}\mathbb{1}_{\alpha_i\times\alpha_j<0}a_j^{BR} \qquad (2)$$

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:

$$u_i(\mathbf{a}, G) = \alpha_i a_i - \frac{1}{2}a_i^2 + \beta\frac{1}{n_i}\sum_{j\in N} g_{ij}\mathbb{1}_{\alpha_i\times\alpha_j>0}a_i a_j + \gamma\frac{1}{n_i}\sum_{j\in N} g_{ij}\mathbb{1}_{\alpha_i\times\alpha_j<0}a_i a_j + \sum_{j\in N} g_{ij}\theta(i,j) \tag{3}$$

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. Table 10 in Appendix provides the list of hashtags used in the Twitter query. 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.

Finally, I download the list of mutual connections for randomly selected one percent 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 (i) less than 5.000 connections and (ii) 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.[4] 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 *inactive* if she does not appear in the tweets' dataset. She

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

is an *activist* if she appears in the tweets' dataset and an *early activist* if she appears before the first Congress debate in June 2018.

Table 1 summarizes initial nodes' degree distribution. On average, individuals have 412 reciprocal links, but only 97 are activists. 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.

Table 1: Initial nodes' degree

	Peers				Peers of peers			
	N	N_a	N_{ea}	N_i	N	N_a	N_{ea}	N_i
Mean	412	97	45	315	1677	262	108	1415
St.Dev.	509	142	65	401	2677	458	176	2286
Min.	2	1	0	0	1	1	0	0
Median	250	44	19	188	736	84	36	625
Max.	4612	1723	805	3725	27896	3927	1467	24962
Observations								5840

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.

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 a continuous variable $a_i \in (-\infty, 0) \cup (0, \infty)$. 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 continuous variable in the interval $(-\infty, \infty)$.

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, on time and per individual, of peers' activism. 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.

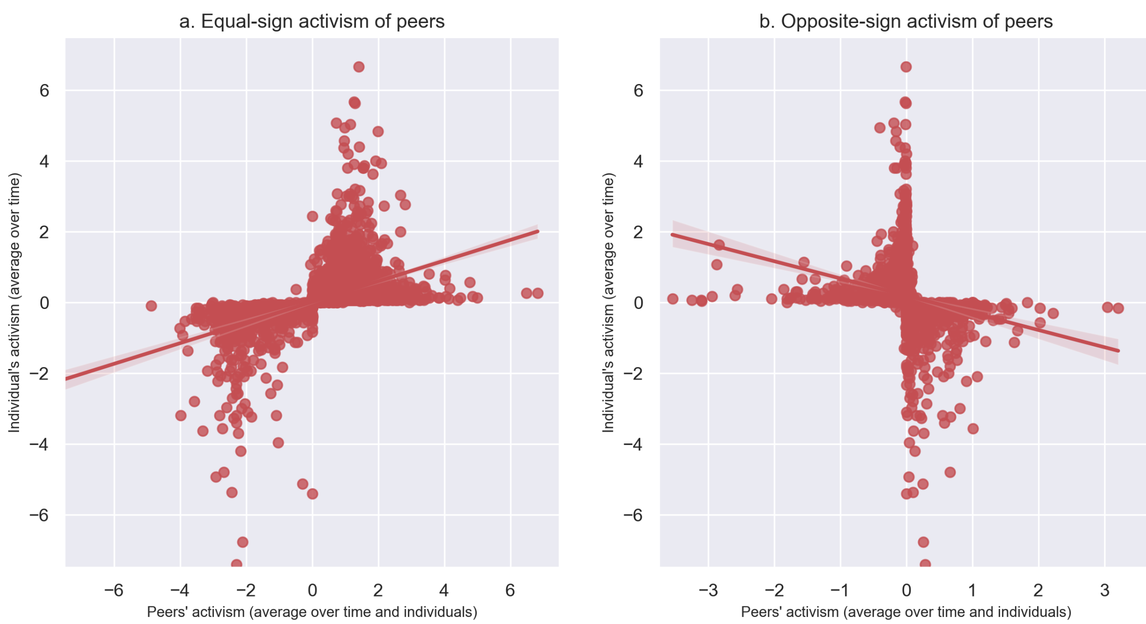
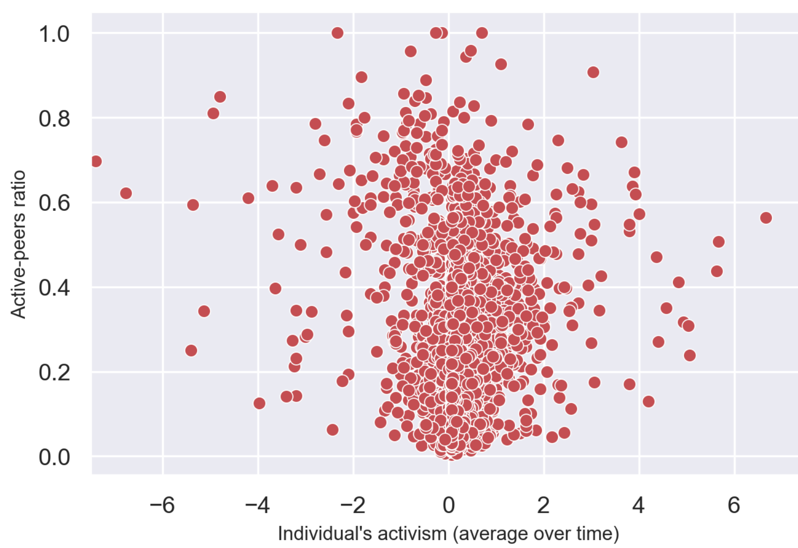


Figure 3 presents the correlation between initial nodes' activism and the ratio of activists in her peers' group. On the y-axis, the variable is the average over time of initial nodes' activism. On the y-axis, the variable is the ratio of active peers over the total number of peers. The differential exposure of initial nodes to activism is one of the sources of variation, at the individual level, in the data.

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



4 Reduced-form analysis

In this Section, I follow an Instrumental Variables approach to estimate peer effects. As described in Section, data is structured as a balanced panel dataset. The individual variable is an initial node's identifier, whereas the time variable is a day. I observe her activism level for any initial node, including dates in which she was inactive on Twitter; in that case, $a_i = 0$.

To estimate the peer effects parameters, I rely on the partially overlapping network's property. Given that individuals interact in a social network, the peer group of any individual i, P_i, is specific to her. Two connected individuals, i and j such that $g_{ij} = 1$, have different peer groups, P_i and P_j. Importantly, the existence of *intransitive triads* helps identification of peer effects, as it is shown in the literature, (see (Bramoullé et al., 2009)). An intransitive triad between individuals (i, j, k) exist if for the pair of individuals (i, j) there exists an individual k who is connected to j but not to i. That is, $g_{ik} = 0$ and $g_{jk} = 1$.

For any individuals i and j, I define $P_{j/i}$ as the set of individuals k who form intransitive triads with them. That is, $k \notin P_i$, and $k \in P_j$. If i is an initial node and j is her peer, I use the average activism of individuals on the set $P_{j/i}$ for all peers $jinP_i$ as an instrument for activism of peers, those in P_i. The identifying assumption is that the activism of peers of peers who are not directly connected to an individual only affects her activism through the activism of peers.

Given the available data, two remarks are essential. First, the instrument is the sum of activism of peers of a 1% randomly selected sample of peers, net of them. That is, I observe activism from users included in a 1% of the sets $P_{j/i}$. Second, estimate peer effects for a subsample of the Twitter population: those who participated in the online abortion-rights debate. Although interesting, the estimation of peer effects on the participation decision is out of the scope of this paper. That estimation would probably require matching Twitter data with other data sources, which is against Twitter's terms and conditions.

The parametric specification of 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, 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 ϵ_{it} is and *i.i.d.* error term with variance σ^2.

Table 2 presents the peer effects estimates by Fixed Effect and Fixed Effect Instrumental Variable models. In all the specifications, results indicate the existence of complementarities in online activism. The comparison between FE and IV-FE estimates, in columns (1)-(2) and (3)-(4), respectively, suggests these complementarities are more substantial when estimated by the IV-FE model.

Coefficients of equal-sign activism levels are positive and significant. For instance, FE estimates in column (1) indicate that a 1-tweet increment on the equal-sign activism of peers increases initial nodes' activism by 0.24 tweets, on average. Coefficients of opposite-sign activism levels are negative and significant, except for column (3). 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).

Table 2: Peer effects in online activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
	Dep. Var.: activism			
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	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)
Controls		X		X
LegDays FE		X		X
Nº Observations				174,238
Nº Individuals				5,808

Note: Robust standard errors 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. * p<.05, ** p<.01, *** p<.001.

4.1 Heterogeneity analysis

Table 3: Peer effects in online activism. Initial nodes with a heterogeneous peers group.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
	Dep. Var.: activism			
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	0.237***	0.187***	0.521***	0.416***
	(0.016)	(0.016)	(0.040)	(0.041)
$\text{activism}_{\text{peer}}^{\text{opposite-sign}}$	-0.164***	-0.162***	-0.145	-0.260**
	(0.042)	(0.042)	(0.094)	(0.099)
Controls		X		X
LegDays FE		X		X
Nº Observations				100,499
Nº Individuals				3,350

Note: Robust standard errors in parenthesis. Balanced panel dataset, daily observations for one-week periods centered on legislative days. Sub-sample of initial nodes whose group of peers includes equal-sign and opposite-sign activists. Specifically, the necessary condition is that the average over time of opposite-sign activism is <0.02, in absolute value. 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 4: Peer effects in online activism. Exposure to activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
	Dep. Var.: activism			
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	0.099***	0.050***	0.384***	0.193***
	(0.010)	(0.007)	(0.031)	-0.039
$\text{exposure} * \text{activism}_{\text{peer}}^{\text{equal-sign}}$	0.199***	0.178***	0.198***	0.252***
	(0.030)	(0.024)	(0.057)	-0.052
$\text{activism}_{\text{peer}}^{\text{opposite-sign}}$	-0.080***	-0.068***	-0.326**	-0.509***
	(0.018)	(0.016)	(0.111)	-0.117
$\text{exposure} * \text{activism}_{\text{peer}}^{\text{opposite-sign}}$	-0.281**	-0.309**	0.124	0.071
	(0.108)	(0.108)	(0.382)	-0.352
Controls	X		X	
LegDays FE	X		X	
Nº Observations				174,238
Nº Individuals				5,808

Note: Robust standard errors in parenthesis. Balanced panel dataset. Daily observations for one-week periods centered on legislative days. Exposure is a dummy variable that takes value 1 if 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. * p<.05, ** p<.01, *** p<.001.

5 Structural estimation

****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:

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

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 Figures

A.1.1 Own and peers' activism levels

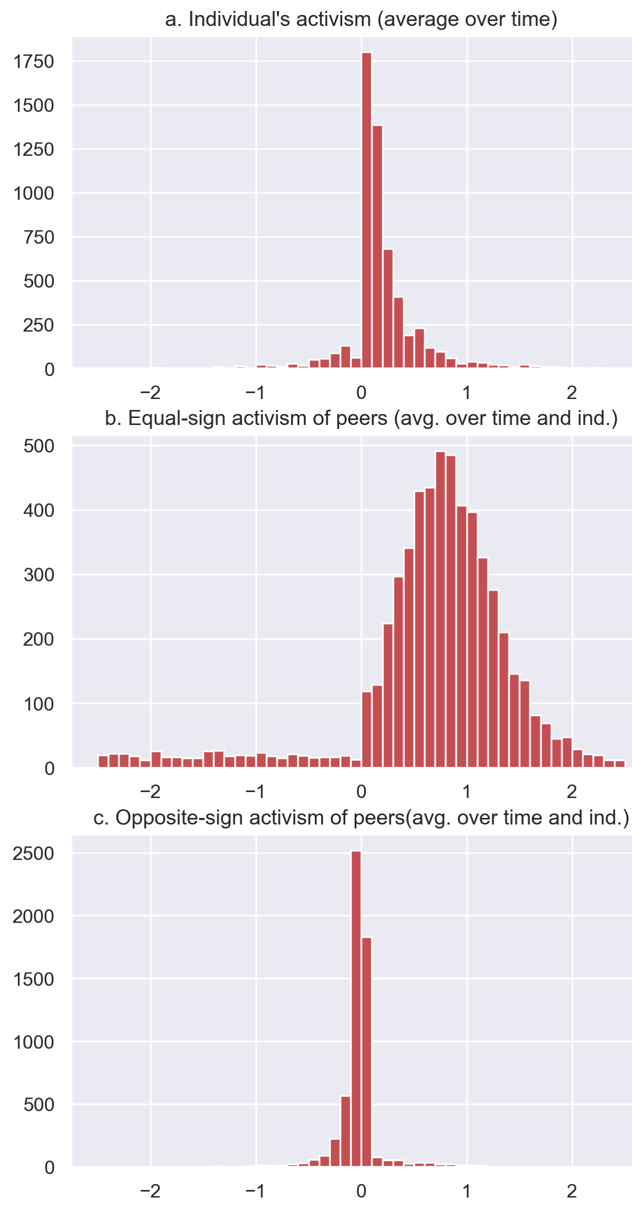

Figure 4: Histograms of average activism levels of initial nodes and their connections.

A.2 Tables

A.2.1 Descriptive statistics

Table 5: Descriptive statistics

Variable	Mean	Median	S.D.
activism	0.3050	0.1667	0.4497
$\text{activism}^{\text{equal-sign}}_{\text{peer}}$	0.9133	0.8371	0.5395
$\text{activism}^{\text{opposite-sign}}_{\text{peer}}$	-0.0814	-0.0241	0.2044
$\text{activism}^{\text{equal-sign}}_{\text{peer of peer}}$	0.8035	0.8142	0.6090
$\text{activism}^{\text{opposite-sign}}_{\text{peer of peer}}$	-0.1561	-0.0475	0.3265
activism	-0.6527	-0.3000	1.0549
$\text{activism}^{\text{equal-sign}}_{\text{peer}}$	-1.5452	-1.4492	1.1613
$\text{activism}^{\text{opposite-sign}}_{\text{peer}}$	0.3567	0.2186	0.4109
$\text{activism}^{\text{equal-sign}}_{\text{peer of peer}}$	-0.9518	-0.8989	0.8508
$\text{activism}^{\text{opposite-sign}}_{\text{peer of peer}}$	0.4669	0.3580	0.5291
$\text{active/inactive}_{\text{peer}}$	0.2364	0.2067	0.1594
$\text{early act/active}_{\text{peer}}$	0.4480	0.4545	0.1650
$\text{active/inactive}_{\text{peer of peer}}$	0.1575	0.1318	0.1228
$\text{early act/active}_{\text{peer of peer}}$	0.4193	0.4259	0.1693
Observations			5480

A.3 Reduced-form estimates.

A.3.1 Early peers as instrument

Table 6: Peer effects in online activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
	Dep. Var.: activism			
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	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)
Controls		X		X
LegDays FE		X		X
Nº Observations				174,238
Nº Individuals				5,808

Note: Robust standard errors 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. * p<.05, ** p<.01, *** p<.001.

Table 7: Peer effects in online activism. Early-exposure to activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
	Dep. Var.: activism			
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	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
Nº Observations				174,238
Nº Individuals				5,808

Note: Robust standard errors in parenthesis. Balanced panel dataset. Daily observations for one-week periods centered on legislative days. Exposure is a dummy variable that takes value 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. * p<.05, ** p<.01, *** p<.001.

Table 8: Peer effects in online activism. Non-zero values.

	OLS		IV	
	(1)	(2)	(3)	(4)
	Dep. Var.: activism			
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	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
Nº Observations				27,652
Nº Individuals				5,808

Note: Robust standard errors 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. * p<.05, ** p<.01, *** p<.001.

Table 9: Peer effects in online activism. Early-exposure to activism.

	FE		IV-FE	
	(1)	(2)	(3)	(4)
	Dep. Var.: activism			
$\text{activism}_{\text{peer}}^{\text{equal-sign}}$	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
Nº Observations				174,238
Nº Individuals				5,808

Note: Robust standard errors in parenthesis. Balanced panel dataset. Daily observations for one-week periods centered on legislative days. Exposure is a dummy variable that takes value 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. * p<.05, ** p<.01, *** p<.001.

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

Argentine Congress has debated a bill to legalize abortion on request in 2018 and 2020. Specifically, days with legislative activity were June 13th and August 8th, 2018, and December 10th and 29th, 2020. Figures 5 and 6 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.

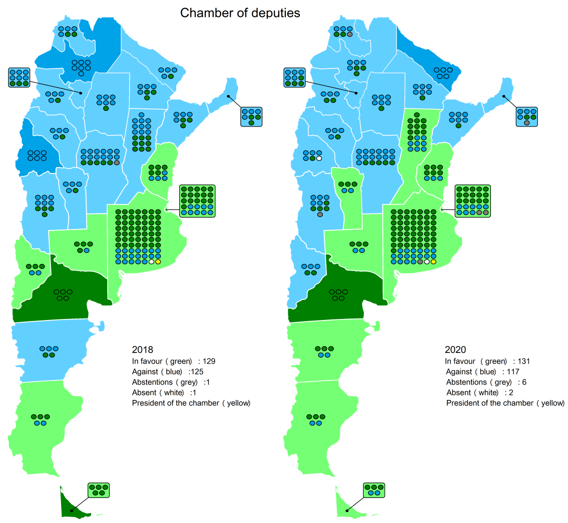

Figure 5: Votes in the Deputies Chamber by provinces, 2018 and 2020.

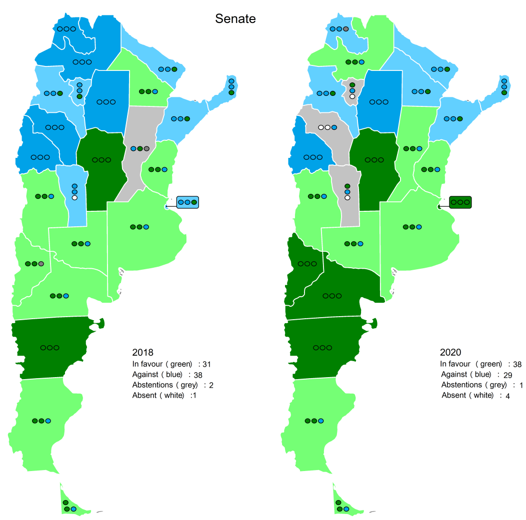

Figure 6: Votes in the Senate by provinces, 2018 and 2020.

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 7 presents the Argentine map with the respective information.

Figure 7: Adhesion to the ILE protocol, 2015.

Figure 8 shows the handkerchiefs designed by the pro-choice and pro-life activists, respectively, in Argentina.

Figure 8: Pro-choice (left) and pro-life (right) handkerchiefs.

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 request. Figure 9 presents the World map with information about abortion access in 2021.

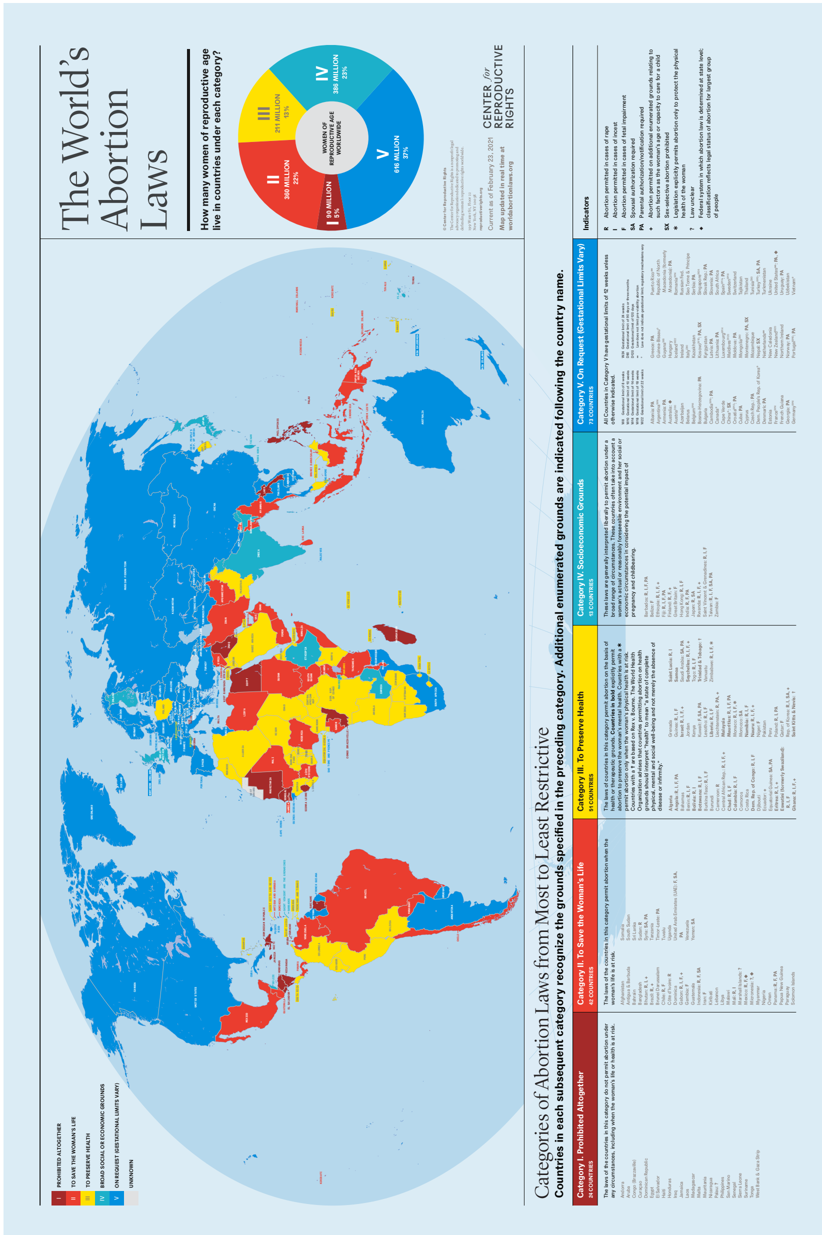

Figure 9: World's abortion laws map, 2021. Source: Center for Reproductive Rights.

A.5 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.

A.5.1 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 10.

List of hashtags	
For abortion legalization	Against abortion legalization
#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.	

Table 10: List of hashtags considered in the Twitter query.

A.5.2 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.