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Abstract

This paper focuses on the subject of protest's international diffusion given the rising levels of production of protests by Latin American countries in the last few years. We consider a protest as public demonstration of disapproval or objection to an official policy. We find a positive association in the production of protests between countries and cannot discard the possibility of contagion amongst them. Using contiguity matrices borrowed from the spatial econometrics literature we find that for contemporaneous protests, news transmitted via the internet are the most likely means of transmission in most countries. Regarding lagged news reports, we find that trade and, to a lesser extent, border proximity become more important. More research is necessary to discern causality.

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1 Introduction

In its simplest acceptation, a protest is a public demonstration of disapproval or objection to an official policy or action (*Protest: Definition*, 2020). Such a demonstration may be a nonviolent action or resistance, civil disobedience (of the law) or even a riot, defined to include violence in differing degrees[1]. Within a country, disagreements between the government and population are not uncommon, therefore the occurrence of protests is not extraordinary.

Different disciplines have given different explanations to the occurrence, persistence and size of protests, though mostly at the individual level: rational choice theory, political network, democracy and trust crises, just to mention a few. These theories, though focusing on different aspects, agree that individuals tend to protest with greater probability if they expect other individuals will also do it. More recently, the study of diffusion of protest has been more prevalent, but there is contrasting evidence regarding whether they diffuse or not.

As shown in Map 1, the close of year 2019 was active for protests in the Latin American region. Observing the temporal progression of the maps, protests seemed to have "moved" from the top right corner to the bottom left one. Many factors could be responsible for this peculiarity, including the internal behavior of each country, but at first glance international diffusion cannot be disregarded.

It has long been proven that peer or neighbor effects are relevant, in education (De Melo (2014), Zimmer and Toma (2000), Henderson, Mieszkowski, and Sauvageau (1978), Evans, Oates, and Schwab (1992)), in public policy (Brueckner and Lee (1989), De Bartolome (1990)), and also when it comes to protests and other forms

[1] A **riot** is a form of civil disorder commonly characterized by a group lashing out in a violent public disturbance against authority, property or people. Riots typically involve theft, vandalism, and destruction of property, public or private.

of collective behavior (Granovetter (1978), Haukass (2012), García-Jimeno, Iglesias, and Yildirim (2018)). These neighbor effects are usually studied at the community, household or individual level. However, with the expansion of globalization and the growing penetration of smartphones and the internet, it can be argued that the definition of neighbor has widened.

Most Latin American countries share an institutional background (Acemoglu & Johnson, 2005), language and increased capital mobility. It can be argued that, like students who share a classroom, countries can be thought of as peers or neighbors, though in a broader sense.

In light of the unrest that has taken place in Latin America during 2019, is it possible that neighboring countries are affecting the number of protests that take place in them at the country or "aggregate" level? Could there be neighbor effects that increase the level of protests or riots in another country? And what possible mechanisms might make this possible?

We find that the data supports the possibility that there exists protest contagion across this set of countries. We find positive association between the number of protests produced in a country i and the number produced in a different country j, contemporaneously. If countries move together, the chance of contagion with each other cannot be dismissed.

Borrowing from the imperfect information literature we posit that the information a country i receives of protests produced by country j might affect the production of protests in i. To explore this possibility, we use data from the production of protests and the news a country receives, combined by spatial econometrics techniques to explore possible different types of neighborhood and transmission mechanisms.

We find that mechanisms might change from country to country and depend on timing. For a contemporaneous transmission, internet penetration is the most relevant instrument for most countries in the sample, though trade and Facebook friendships are also relevant to a smaller number of countries. Regarding lags in transmission, news from a trade partner are associated with a higher level of protests one month later. In addition, news from both trade partners and geographical neighbors are associated with a higher level of protests two or more months later.

Section 2 is the literature review, section 3 discusses the data analysis, section 4 tackles the empirical challenges and strategy, results are in section 5, complementary analysis and conclusions.

2 Literature review

The literature on protests and social movements takes place mainly in the sociological context. Social movements are diverse and pursue a variety of goals, but for Knoke (1990) they involve at least four common elements. The first refers to socially disruptive actions that target public authorities and their symbols. Second, social movements use primarily purposive (as opposed to emotional) tactics that seek to change status quo. Third, an emphasis of social organization that stresses group activity rather than individual leadership. The last common element of social movements is that they can incorporate organizations that are distinct from the movement's mass base.

As mentioned before, protests are public demonstrations against an official policy or action, they differ from social movements in that they do not necessarily have purposive tactics that seek to change status quo or an emphasis on social organization. All social movements are protests in some form, but not all protests are social movements.

Keeping in mind the relationship between social movements and protests, we can revise three elements of social movements that can help guide us in the study of protests. First, they behave cyclically, with short bursts of protests that are followed by either success or repression and a long protest-free period. Second, they grow by social homophily, in which individuals tend to interact more with similar people (gender, age, etc.), and closeness with a member of the movement. Finally, the microlevel networks among movement participants are paralleled at the macro level by the linkages between international social movement organizations (Knoke, 1990).

These elements (mainly participation) are also studied by economists at the individual level, but in a different manner. According to Olson (2009), social movements want the government to increase or produce public goods, protests are the strategies they use to accomplish their goals; as is natural for public goods, the free rider and imperceptibility problems must be taken into account by the individual. In the end, protesting becomes feasible when incentives are offered to the individuals willing to protest and reach said incentives.

A first departure from Olson's original model ((Tullock, 1971), (Silver, 1974)), concludes that the public good values from joining a revolution may be negative and the private gain might be the main motivator to initiate or participate in such. From Tullock and Silver, increasing public goods production is not the only reason for joining a revolution, private gain becomes the focus.

Granovetter (1978), though not an economist, made a significant addition to existing literature: he includes n, the number of people participating in a collective action, as a predictor of participation. When choosing whether to participate or not in a protest, the costs and benefits vary with the amount of people that will choose a given alternative; there is a threshold, after which the benefits of participating exceed the costs. This is a good precursor to more in-depth behavioral economics analysis. From this point, not only public goods and private gain are relevant to study protest participation, the number of people set to participate is also a relevant factor.

Amongst others, behavioral economics have opted for a "dual-process model" (Kahneman, 2005), in which two cognitive processes can coexist: intuition and reason. In situations of high stress, like protests or riots, an individual might lose the ability to use reason and will only use intuition, disregarding long term consequences of participation. A new level of complexity is added here, to define participation not only do economists look at public goods, private gain and the number of participants, but the emotional state at the time the protest takes place.

It is a long-standing fact in economics that individuals make their decisions based on information, participation in protests is not an exception. An individual's personal characteristics (age, sex, education level, salary, etc.) can become a source of grievances perfectly known to him, but the information he receives about society as a whole can add or subtract to his particular misgivings.

Since protests rarely occur spontaneously, it is implied that a certain level of collaboration or information sharing must take place before the protest. After the occurrence of the Arab Spring set of protests in 2011, there was an increased interest in how these demonstrations came to be and spread to much of the Arab world. Many researchers agreed that the spread of information played a fundamental role, particularly social networks like Facebook or Twitter (Tufekci & Wilson, 2012).

Given the complex nature of protests, most studies have been done in a specific protest or set of protests and usually at the individual or national level (x factors in i country produced y result in i). Recent literature using large multi-country datasets has filled this gap somewhat, in particular, research about the importance of social media for protests at the national level (Fergusson & Molina, 2019). They find "that Facebook has had a significant and sizable positive impact on citizen protests". The importance of social networks in modern day protests (Koltsova, 2019) has also been analyzed by researchers.

Other studies have focused on the effects of more traditional means of communication on protests. García-Jimeno, Iglesias y Pinar (2018) used railroads (main form of information deli among cities in the 1800) to study the diffusion of protests at the State level in the United States. They find that railroad and telegraph mediated information about neighboring protest activity were main drivers of the diffusion of the protest movement.

Andrews y Biggs (2006) used news and tv (for the 1960 sit-ins). They conclude that social networks (in the traditional sense, since not Twitter nor Facebook had been created yet) have little effect in diffusion among cities, while news and tv played a major role.

Not many have tried to empirically explain if the diffusion observed at the sub-national level also exists at the international one, though Castells[2] (2015) mentions the effects of a connected world on the contagion of protests[3]. We posit that since

[2] For Castells (2019), people's ideas change faster than the governments and institutions can keep up with, therefore protests are bound to happen to correct such discrepancies. However, in a world where ideas can travel seemingly instantaneously between borders, it is logic to think that the discrepancies can also move borders and infect other countries. If "the microlevel networks among movement participants are paralleled at the macrolevel by the interorganizational linkages in social movement organizations and their sponsors" (Knoke, 1990), then this should also happen at the country level. His explanation for this contagion is the rupture of the relationship between those who govern and the governed (2018), there is a lack of trust in institutions that has been observed all over the world, "it is a [rejection] of liberal democracy as it exists in each country" (Castells, 2018).

[3] "The movements spread by contagion in a world networked by the wireless Internet and

globalization[4] has continuously decreased barriers between countries, especially in terms of information, diffusion takes place between borders: protest contagion between countries[5] must be happening. We set upon finding indications that this is the case as well as exploring the means through which this phenomenon might take place.

Latin American countries already have many cultural and social similarities, they share language, a common colonial background (which can be argued to be produce similar institutions (Acemoglu & Johnson, 2005)), religion, among others. With the growing economic integration[6] in the region it is easy to see them as neighbors in a wider sense of the word, especially since the spread of information from one to another is relatively easy with no (almost none) language barrier.

3 Data description

To find out if protest contagion between countries might be occurring, the Global Database of Events, Language, and Tone (GDELT) will be used. The GDELT Project began in 2010 using text parsing to evaluate written online news articles and create a compiling database[7]. Until 2014 compilation had daily frequency, and

marked by fast, viral diffusion of images and ideas".

[4] "Globalization is an on-going process of international integration that results from and supports the interchange of institutions, products, ideas, and culture" (Ashenfelter, Engle, McFadden, & Schmidt-Hebbel, 2018). It is closely linked with integration and generally implies the free movement of production resources: capital, people, ideas and supplies.

[5] Given the independence of the States that conform USA, and the size of the country, it is possible that many cities can be further and more heterogeneous than some countries, though not necessarily Latin American ones.

[6] Some region exclusive initiatives include: Pacific Alliance, Mercosur, Central American Integration System, Organization of American States, Community of Latin American and Caribbean States, Union of South American Nations, Bolivarian Alliance for the Peoples of Our America, among others.

[7] An algorithm 'reads' an article and using a predefined classification of words or phrases (a list of relevant people and organizations for actors in an event, verbs to classify the actions described in the article, among others) and categorizes what it read. The event is thus given a unique identifier.

from 2015 it has 15-minute frequency.

GDELT has three main datasets: Events, Global Knowledge and Mentions. Using all three allows assignment of a geographic location to the media source reporting the news as well as to the event that occurred (in our case, a protest). In addition, GDELT provides a "mentions" indicator that indicates how many times each event was mentioned in other articles in the span of 15 minutes since it was first recorded[8].

Two main variables are constructed from this dataset: production of protests and their mentions in the media.

3.1 Production of protests

The occurrence of protests, comes from the Event database, where each article parsed by the algorithm is analyzed and counted as a new event with a unique identification. Since these occur at fifteen-minute intervals, time aggregation is necessary. We do this on both a weekly and monthly basis[9].

A separate issue is that, more populous countries like Brazil or Mexico are naturally prone to produce more protests in absolute number. To capture this effect, we scale de number of protests by the average population between 2015 and 2019, measured in millions. Thus, our main measure of protest news is the number of protest events

The algorithm will continue to read other articles, if enough categories match a previous event (for example who did something, place where it happened, action that took place, etc.), it is counted as a mention of the first event otherwise it is given a unique number and treated as a new event.

[8]This number of mentions exists only in the event database and counts how many times a certain event is mentioned across all sources during the first fifteen-minutes after it happened. This is typically used to get an idea of how important a particular event is, however we are interested only in the mentions taking place in certain sources and will build an appropriate indicator.

[9]Though there have been cases of spontaneous protests, and social networking via Twitter or Facebook has been shown to decrease the time it takes for a protest to be organized, it is unlikely that a protest can be devised and executed in a single day. A week seems like a much more reasonable time frame, especially since we are studying protests at the country level and not a single event. On the other hand, a trimester has too much going on and would leave us with too few observations to analyze the information.

produced in country i at week or month t, per million inhabitants, labeled P_{it}:

$$P_{it} = \frac{Protests_{it}}{\frac{1}{5} * \sum_{y=2015}^{2019} Pop_{iy}}$$

where y is the year the population was reported and Pop_{iy} is measured in millions.

In general, count data like P_{it} ignores the "information content" or the individual characteristics of protests. Given that the dataset is created by an automated algorithm, many subtleties that we would like to study are simply not reliable enough to delve into them. Manually coded datasets might be needed to deal with the nuances inherent to the subject. Still, we believe that this first approximation to the identification of international diffusion, shines light over the contagion issue.

3.2 Mention of protests in the media

The second relevant variable for the analysis is how many times a protest that took place in location j was "mentioned" by media located in i, with $i \neq j$. Unlike Pit, these mentions, that are called "news" from this point on, have been filtered by local media. These media do not report everything that happened internationally since their main value-added comes from selecting the most important news for their audience, saving the audience the effort of reviewing enormous amounts of news to find just a few gold peppers.

This implies that, the number of news do not need to be scaled by population. For example, since Brazilian media already picked the most relevant news about Chile, scaling their number by the Brazilian population (in millions) appears as inadequate.

$$M_{it} = \sum_{j=1}^{J} Mentions_{jit}, with i \neq j$$

where M_{it} is the number of protests news mentioned in country i from protests produced by the rest of the sample, at time interval (week, month) t.

Let's illustrate this with a recent example: let Chile be country i with 1 million inhabitants, the 25th October 2019 demonstration be event x and the only one in that month; let Brazil be country j and on the 26th October two news articles were published by Brazilian newspapers about the 25th events in Chile. In this case, since only event x happened in Chile, $P_{ChileOctober} = 1$. On the other hand, two news articles about Chile were published by Brazilian news $M_{BrazilOctoberChile} = 2$.

Similarly, the variable $M_{ChileOctoberJ}$ counts all news articles published by Chilean registered media about protests produced in the rest of the countries of the sample, while $P_{BrazilOctober}$ means all protests produced by Brazil on the month of October per million inhabitants.

The information an individual receives is the number of protests that occurred in another country reported by local press. This will directly underestimate the amount of information received, as international news outlets might add their own reports about the same events. We deem this concern not to be important since the larger media conglomerates have local presence and are mostly picked up by the database algorithm[10].

[10] Given that sources used by GDELT have online presence, it can be hard to classify to which country a specific site belongs. To map the media sources, the algorithm takes the information of events' (protests) location and assigns the source to the country their articles mention as the place of occurrence in the largest proportion. As an example, say cnnchile.com produces 1,000 articles a month, for the sake of simplicity let's assume these are unique events (no two articles report on the same thing), the algorithm will identify the who, where and what of each article. Let's say the where behaves thus: 300 articles talk about events produced by Chile, 100 by Argentina, 150

The information received can also be underestimated if individuals receive second-hand information without intermediation by local media outlets. This source of underestimation cannot be picked by the database. Bellow we propose different avenues that facilitate the interaction between the countries might mitigate this problem.

3.3 Other relevant information regarding the dataset

The database as a whole has several features: first, it is not a census of global events, but of what the media reports. The information the media chooses not to report either based on practical constraints (time, resources, cost, etc.) or based on inherent biases towards some types of events, like protests, is not contained in the database.

Second, media from different countries have different levels of "sensitivity" to smaller events, which might be deemed unimportant for coverage. They will not be included in the database but might alter the predisposition of people to react to outside news and could potentially produce differing distributions functions for our two variables. Thus, there is a measurement error problem, which may be significant.

Let's illustrate this with an example. Chile has one million inhabitants; its citizens have a number of different grievances and in the months preceding October 2019, some of them decided to make small demonstrations in different places of Santiago. In August, five distinct pairs of individuals stood with posters on different days in front of different government offices, protesting for different issues. However, two important bills were passed by the senate on the same day protesters were outside; the media deemed that reporting about the bills was more important than

by Brazil, 100 by United States, 50 by different European countries, 200 by other Latin American nations and 50 could not be allocated. This source (cnnchile.com) will be thought of as Chilean.

reporting about two protesters. In the end, only two of the five made it to the press. Something similar happens in September, but instead of five pairs there are now ten pairs, equally, only a fraction of the demonstrations is reported on the news. When they reach October, the press becomes hyper aware, and protests reach 150 protest per million. It is different to reach 150 starting from 2 or 5 or 15. The variance greatly increases as the starting point decreases, and the peak will seem higher than it is. Since mean and variance are the two most important parameters to evaluate a distribution, under-reporting can skew it.

Another reported problem, unique to this dataset, is the double coding of the same event. Though one would expect to have a unique identifier for a single protest, it might be coded multiple times depending on the wording of the articles. Double or triple coding could be a relevant problem for the results of this paper, but we have no basis to suspect a systematic bias. In any case, time aggregation of the data at weekly or monthly level should eliminate most of this concern.

Another issue is that our database from news does not have data from social media reports. This has been deemed relevant for protest diffusion at the national level in recent literature (Fergusson & Molina, 2019). The database does not tell us if Argentinians and Chileans get together on Facebook or Twitter, discuss their woes or exchange news articles. This data omission might be tied to measurement error.

Given the database is compiled from an algorithm that searches the web for news articles, countries with relatively poor access to the internet (like Haiti or Cuba) or with a mostly censured press (like Venezuela), make for poor observations. Also, countries with very small populations or that are too culturally different, mainly on the grounds of language, have also been excluded.

This paper excludes data from the following countries: Venezuela, Haiti, Cuba, Guyana, Surinam, French Guyana, Jamaica[11] and the Lesser Antilles. The sample has a total of 17 countries with data between the years 2015 and 2019, for 260 weeks or 60 months, around 5,000 or 1,000 observations respectively. After reducing the scope of the database to the larger Latin American countries with access to the internet, which all have similar characteristics, there is not necessarily a need to account for distinct media sizes directly, deflating by the population is deemed sufficient to relativize the variables.

4 Empirical challenges

Protests are complex. One could posit that the occurrence of a protest is a deviation from an internal equilibria within each country, with three sets of players (government, businesses, general public), where each one (or a fraction of them) either wants to preserve or break the status quo. This system is in perpetual movement, oscillating between calm and unrest. The duration of these oscillations might be different for each country, but there are many forces that interact. From outside the system each country can only observe the state of his neighbors' system and this could tip his own system to change states.

Implied in the preceding paragraph is the fact that there are many variables that influence protests and the local context of each country is important. Consider the challenges faced by a simple linear regression such as $P = M'\beta + \varepsilon$ estimated by OLS. The first complication is the endogeneity evidently present in M: there are many omitted that can be correlating with M. In addition, there might be measurement error in the database and a degree of reverse causality[12] between P and M might

[11] English, with its Germanic roots, is deemed more different from Spanish (the dominant language of the sample) than Portuguese, which shares its Latin origins and has a degree of intelligibility with (Laso, 1996). Under this assumption, Brazil enters the sample, while Jamaica and Guyana do not.

[12] It is possible that a sudden increase of protests on i can change the media focus of j, in which

exist. Therefore, such a model is unlikely to tell us anything about the effect protests on j (or the protests on j perceived by i) have on protests on i.

Following Manski (1993), there are many possible sources of endogeneity when working with neighbor or peer effects: "endogenous effects, wherein the propensity of an individual to behave in some way varies with the behavior of the group; exogenous (contextual) effects, wherein the propensity of an individual to behave in some way varies with the exogenous characteristics of the group, and correlated effects, wherein individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments".

This endogenous effect is what we could identify as the contagion parameter, to help mitigate some of the endogeneity problems, we first propose the following specification:

$$P_{it} = \alpha + \beta M_{it-k} + \rho \sum_{l=0}^{L} P_{it-l} + \eta_i + \theta_t + \gamma_{it} + \varepsilon_{it} \tag{1}$$

P_{it} represents the number of protests (as defined in the preceding section) produced by country i at time t, M_{it-k} refers to information on protests produced by all countries of the sample except i at time $t-k$ and reported in country i simultaneously (at time $t-k$), P_{it-l} are the protests that were produced in country i at time $t-l$, with l running from 0 to L. Parameters η_i and θ_t are fixed effects at the country and time-unit level. γ_{it} is an interaction between the two. Since conventional covariates (like unemployment level, GDP, population, education level, etc.) have lower frequencies than the data collected here, it was not deemed important to include these in equation 1, and in any case their variances should be captured by η_i.

case protests that usually would not be reported or mentioned are brought to attention.

Using M_{jit-k}, lagged at least one period mitigates the reverse causality that might be present in the data. Also, by definition, the fixed effects at the country level and its interaction with the time variable should incorporate all the variation present in each country (which alleviates the omitted variable bias and accounts for any ongoing trends within the countries), fixed effect at the monthly level lessens the correlated effects.

There might be exogenous phenomena occurring at higher frequencies than those studied (hourly, daily, weekly), particularly in countries that mostly depend on the trade of commodities. A significant short-term shock might affect the occurrence of protests (i.e. a sufficiently large oil price shock might increase protests in countries that import it and decrease in countries that export it).

Ideally, working with dynamic panels at high frequency, after incorporating the corresponding fixed effects, should take care of most sources of endogeneity, but protests events might take longer to develop than one period in which case no effect will be found. One method to get rid of such pervasive endogeneity is to use an instrumental variables approach. No exogenous variation was found that affected all countries and did not confound the data.

On the other hand, since the data refers to places and not people, another form of dependency within outcomes needed to be considered. Using spatial analysis with more descriptive methods was the best approach to also consider the spatial dimension of the contagion of protests.

4.1 Spatial analysis and propagation mechanisms

Going back to the elementary linear regression model $P = M'\beta + \varepsilon$, we want to know how much one country affects another. Climate and terrain conditions have a long history of being associated with conflict (Almer, Laurent-Lucchetti, & Oechslin, 2017; Burke, Miguel, Satyanath, Dykema, & Lobell, 2009; Harari & Ferrara, 2018). Both are intrinsically dependent on geographical location. For example, Arica and Tacna might be part of Chile and Peru respectively, but they share many geographic and historical characteristics. A drought in the area could equally affect farmers on both sides of the border, and both might respond by organizing a protest to their respective governments. Contagion may have a geographical dimension.

Given equation 1, some, if not most, of the conventional endogeneity is accounted for, but including the spatial dimension might allow us to explore a natural method to restrict the way observations connect (Gibbons & Overman, 2012). This can be achieved by borrowing the concept of "contiguity matrix" from the spatial econometrics literature.

When thinking about the way two places can be geographically connected, one of the most intuitive ways is when they share a border. It is possible to build a vector for each country i that contains a 1 in cell i,j if i shares a border with country j. This reasoning can be extrapolated to other forms of connections. Taking a vector W_{ij}, whose jth element has a bigger value the more closely j is connected with i, and stacking them together to form a matrix yields another the contiguity matrix.

Weighting (pre-multiplying) the variables of interest by a matrix that summarizes a given aspect of the interaction between countries i and j, allows measurement of which type of interaction associates more closely with the outcome variable. Contiguity matrices can be built in many ways. Depending on their structure, the interpretation results might be different.

Two important factors to take into account when building a contiguity matrix are: whether the diagonal will be included (which allows i to relate to itself) and if the matrix will be row normalized (dividing each cell of a row by the total of cells with data in that row -averaging-, this allows the resultant parameter to become the overall change in i attributed to all its neighbors). For this research main diagonal will always be 0, as we want the association between i and j exclusively, and rows will not be normalized to get the marginal effect of the change in one neighbor.

To test for the different mechanisms that may allow the transmission of protests, the following contiguity matrices were built (see Annex):

- Border: is a binary contiguity matrix that takes the value 1 when country i shares a border with country j. As explained before, this is the conventional use for a contiguity matrix. It is implied that the proximity with a neighboring country creates intricate dependencies between the two, particularly in neighboring towns. Since this matrix is binary it means Chile would only pay attention to news coming from Argentina, Bolivia or Peru and no attention to the rest. If this were the only mechanism through which protests diffuse a country like Dominican Republic would not experience diffusion from any of the sample countries.

- Distance: is the inverse of the distance in kilometers from the centroid of each polygon of the map of country i to the centroid of the map of each country j (scaled by 1,000KM). The inverse guarantees that the closer two countries' centroids are the more weight will be given to that interaction. $\frac{1}{dist_{ij}} * 1,000$ This logic is similar to the previous point, but this matrix is no longer binary. It is expected for Chile to pay more attention to news coming from Argentina or Peru than from Colombia or Ecuador. In any case, some attention is paid to all members of the sample.

- Internet access: this was built from a vector that has the proportion of the population of country i that has access to the internet. This number is equivalent to the probably that any given individual in country i connects to the internet. Assuming that these probabilities are independent for i and j (i.e. internet connection in Argentina does not affect internet connection in Bolivia), the product of these proportions gives us the probability that an individual from i connects directly to one from j at any point in time. Since practically all news travels through the internet, scaling the information reported from country i to country j by the probability that they can connect may get us closer to the real penetration of the news between i and j. The proportion with access to the internet was determined by averaging between the three years 2015-2017[13].

- Youth proportion 15-34: similar to the internet access, this weight was built from a vector that has the average (2015-2019) proportion of the population deemed young (between 15-34 years old) in each country. Assuming the same principle of independence for the data between i and j, we multiply $i * j$. The intuition for this relates to the fact that protestors tend to be young, the larger the young part of the population is, the more receptive should be to protest information.

- Active labor force proportion 15-64: is the same as the previous matrix, but these numbers come from the demographic definition from economically active population excluding older people most of whom are retired (those under 15 and over 64).

- International trade: this is built as the commercial openness index between i

[13]This data comes from household surveys that ask if the individuals have access to the internet in their homes. The sample for this paper is 2015-2019, however data is not available for all countries for the complete sample. The three observations that were common for e country were averaged to use a single measure for the complete sample, as opposed to using yearly matrices on 60% of the data.

and j $\frac{imports_{ij}+exports_{ij}}{GDP_i+GDP_j} * 100$, scaled by 100 to facilitate reading the numbers. The idea behind this contiguity matrix is to find out if countries are more receptive to react to news coming from their closer commercial partners than from others. This and the binary matrices are the only three that are not symmetric, in the case of international trade, asymmetry derives from the fact that exports are reported at Free on Board (FOB) prices while imports are reported at Cost Insurance and Freight (CIF) prices.

- Social Connectedness Index: developed by Bailey, Cao, Kuchler, Stroebel, & Wong (2018) with Facebook data. They took an anonymized snapshot at 2020 of Facebook users and their friendship networks and created an index that measures the connections between Facebook users from countries i and j. $SCI_{ij} = \frac{FBconnection_{ij}}{FBusers_i * FBusers_j}$. The index has been standardized to go from 1 to 1,000,000,000. The logic for this matrix should be obvious, since the more connected are i and j, the more their protest information should influence each other.

- Severest protests: this is a binary matrix or rows i and columns j. For each country i at time t, it has a 1 in the country j with the largest proportion of protest news reported in i, i.e. the main contributor to the news reported in i that period. If Nicaragua received 10 reports from the rest of Latin America at period t, 5 from El Salvador, 3 from Honduras, 1 from Panama and 1 from Mexico, that period's matrix on Nicaragua's row would have a 1 at El Salvador's column and 0 everywhere else. This is the only dynamic matrix considered here. The underlying logic is that people at country i will concentrate their attention completely on the news coming from the most reported country j. This is a plausible assumption since media tends to focus on particular subjects and it is not uncommon for the people's attention to focus where the media does.

It is important to note that though there is a logic to each one of these matrices, the specific numbers in a matrix do not need to have a meaning of themselves. The relevant information is contained in the relative weights generated by combining these numbers.

5 Results

The main question is how the association between protests and news changes as they are weighted in different ways. A first result is that weekly and monthly aggregation turned out to be virtually the same. This important result allows us to report everything at the monthly level, to increase comparability with similar studies. We do this from this point on.

We begin by examining the distributions of the data. Some facts can easily be discerned in Figures 1-4: there is a lot of variance in the data. When looking at the average and total monthly protests and comparing those to the individual countries' protests, though they resemble each other, there are a lot of outliers that mostly coincide with periods of turmoil in particular countries. This is not undesirable since we want to capture this variation. However, the fact that countries like Nicaragua, Colombia and to a lesser extent Chile have such high peaks even after controlling by population, might skew the overall relationship.

The average and total monthly protests have a positive trend in the period, though for most countries the period has been relatively stable. Some countries have a clear and strong positive trend and others a strong negative one. Trends might pose problems when we look at measures like Pearson's correlation coefficient, which are not sensitive to magnitude.

The distribution of the total monthly protests, in Figure 3, resembles a Pareto Distribution with a high α coefficient. The individual ones in Figure 4 have varied shapes, though most seem to be log-normal or χ^2. Only a few countries resemble the Pareto distribution of the total. A different transformation was required to normalize each country's distribution. Because the focus of this paper is not modeling causal relationships, we chose to analyze them as they are, so no normality assumptions are imposed.

The fact that the different distributions don't always resemble each other could imply that whatever holds true for one country needs not hold for the rest. With that in mind we look to analyze diffusion at the aggregate and country level.

To complement the visual analysis from Map 1, in Table 1 we calculate the correlation coefficient for the monthly production of protests in each country of the sample. It was found that the average time it takes since a protest occurs and a news article reporting it in a different country comes out is 1.2 days on average. This short period makes contemporaneous diffusion not only possible, but likely.

The results in Table 1 are contemporaneous correlations. All countries, except Guatemala, exhibit at least moderate correlation (from 0.3 to 0.5) with at least one other country. Bolivia, Chile, Colombia and Ecuador exhibit strong correlation with at least one country. Bolivian protests have a strong correlation with Chilean and Colombian ones.

As seen in Tables 2 and 3, this analysis was repeated for lagged protests (one country at a time). Every column in those tables show correlation of the country's respective lag with the rest of the countries in t. For Table 2, association between protest occurred in country i in a month and protests occurred in country j the preceding month, is much diminished in comparison with contemporaneous association. Only in the case of Ecuador in $t-1$ with Bolivia and Chile in t, did it show a very strong association, the rest of the countries exhibited moderate association at best.

These results show that some countries do move in the same direction, when using lags it was more discernible who precedes who. Taking Bolivia as an example, when lagged (month $t-1$) its association with Chile and Colombia at month t is halved. This might imply that Bolivia looks at Colombia and Chile, not the other way around (Chile in $t-1$ keeps a strong association with Bolivia in t).

When analyzing the association between protests occurred two months in the past and current ones, Table 3, few moderate correlations remain. The only notable exception seems to be protests in Mexico from two months before being strongly and moderately associated with current protests in South American countries (Argentina, Paraguay, Uruguay and Peru).

Next we examined the descriptive statistics for the total number of monthly protests produced in a country. One thing that the reader might notices is that the observations for the first year are fewer than for the following years. This happens because the GDELT database began the 15-minute interval collection on February 2015. Since a large jump in the number of reports occurs from February onwards, the data for January is excluded from the database.

As expected from the distribution analysis and as shown in Tables 4 and 5, patterns are not evident when working at the aggregate level. As confirmed by Figure 1, the mean shows a positive trend. This trend is based on the low starting level in 2015 with 14.1 monthly protests.

The logic of looking at news reports as possible explanatory variables is similar to Lucas' islands model of inflation (1972), where an individual lives in an island, produces a single good y and his price-changing decisions are based on imperfect information. If no information from the outside is obtained, the individual's decision will be entirely endogenous; however, if he observes the decisions of individuals located in other islands (the number of protests in a given time period) he may change his own decision to protest. This could happen, for example, if he believes the other's decision signals a more welcoming context for his demands and therefore a greater probability of success, or a lower expected cost of protests.

5.1 Main results on contiguity

Tables 6-8 provide the main results of the paper. In Table 6 we can see the association between monthly protests in each country and the news reports at time t, weighted by seven contiguity matrices. This is the correlation between this month's protests in i vs this month's news reports in i about j. As shown by Table 6, not all countries have a strong association with the weighted news they receive, but in all cases the association is enhanced by the weighting.

It is indisputable that for most countries the stronger contemporary association of protests exists with news weighted by internet access. This is an expected result since the internet is the mechanism that allows them to find out the news so quickly (contemporaneously). The contiguity matrices for Facebook friends and international trade also show strong association with other countries, though not always the strongest.

Since Facebook works over the internet, it is hard to expect it to outperform the internet itself when considering joint access (for i and j) to the web. This goes against recent studies that say Facebook is an important channel that improves organization of people and diffusion of movements.

For other studies Facebook access was the only variable used to gauge the ability to make connections and exchange information with other countries or territories. This indicates that perhaps other ways to measure internet connections should take a more prevalent role when studying protests and conflict.

Figures 5 and 6 display the graphical association between the countries and the largest presumptive contemporaneous mechanism. As shown in Figure 5, the strongest association occurs for Costa Rica with international trade, followed by Bolivia with internet penetration, Chile with the Social Connectedness Index and Ecuador also with internet penetration.

Countries with the largest average internet penetration (Argentina and Chile) have the Social Connectedness Index as the main contemporaneous mechanism, while those with the smallest internet availability (Nicaragua and Honduras), seem to use the internet itself. This is interesting and not unexpected. Internet is necessary to use Facebook, which according to the literature is an important contemporaneous mechanism, however it seems to be more effective in highly connected countries. This is congruent with the finds of Fergusson and Molina (2019).

Figure 6 shows the same contemporaneous mechanism for each country as Figure 5, but in equally sized groups, mostly deciles. Each box shows the distribution of monthly protests within the weighted news variable group. Large bars indicate more dispersion than smaller ones. It is easy to see that for countries like Bolivia, Chile and Ecuador, though there seems to be a positive trend, one large bar indicates much dispersion, as confirmed by Figure 5. This indicates that the large association these countries have with their respective weighted news, could be driven in part by outliers and calls for caution when interpreting the results.

Another important result appears when measuring the association between protests in month t with weighted news in month $t-1$. Having done its job contemporaneously, internet is no longer the most important mechanism for transmission. In month $t-1$, more countries seem to pay more attention on their trading partners than anywhere else, though not with the intensity they did in t.

Though most associations diminish when looking at news received in $t-1$, for some countries it becomes stronger. For some cases, the number of protests decreases when a trade partner or a close country experienced an increase in protests in $t-1$ (Table 7), even if they are barely relevant. Though this result seems counterintuitive, it begs to be reminded that protests have social costs. One of them could be that trade partners and close countries diminish their economic activity and that sends a signal to the population to slow down protests to protect jobs or income.

Finally, when looking at lags of two months (Table 8), we find that there is almost no association. Some residual mechanisms occur through international trade and bordering neighbor. There seems to be a change in what people look at depending on the timing. News reported about the neighbors is associated with an increase in protests at least two months later, news about trading partners is associated with an increase in protests one or two months later, whereas internet penetration is associated with an immediate increase in protests.

After three months, association vanishes almost completely, except for Costa Rica. News reports seem highly persistent for this country.

These results are only indicative of what might be lurking underneath. An exogenous source of variation is needed to try and identify a causal effect. However, finding one that affects all countries at the same time and does not confound the results seems hard.

6 Complementary analysis

It is important to investigate if there is significant measurement error present in the database. To assess this, alternate datasets like Armed Conflict Location and Event Dataset (ACLED) could be used to see if the results hold under different data. ACLED uses a different compilation methodology. However, ACLED only has information for protests starting in year 2019, which would imply a much shorter panel that could be compared with only $\frac{1}{5_{th}}$ of the data used here.

Another data source that can be explored to check for the robustness of these results is Google Trends. This system creates a popularity index ranging from 1 to 100 for search terms and is available at subnational levels with much reliability. However, it uses keywords from the search terms to associate events.

ACLED dataset also includes subnational level data. It would be interesting to replicate the models explored here with a finer grid to be able to apply spatial error correction methods, though that enterprise exceeds the reach of this paper. Both datasets have advantages and disadvantages, on the one hand ACLED is more thorough in the revision and categorization of the source data, but it might not be possible to link information in country i with events in country j. Google trends has the ability to link countries, but identifying the events occurred in a particular place will prove a challenge and most likely will need a proxy variable, particularly since all its data is all indexed.

There could also be other ways in which information travels from one country to another. Though unlikely to be more relevant overall, it might be that there is a significant first-hand information exchange. Tourists might disseminate information directly when they travel to other parts, this could be captured by a contiguity matrix built from the international passenger statistics and weighted directly on protests instead of news. In spatial econometrics this is called a spatial lag even if it is done contemporaneously. Likewise, Facebook friends might also exchange direct information. Including these into a more comprehensive model is a possible extension of this work. A Durbin Spatial model would probably be the best approach given we find a way to eliminate endogeneity.

This analysis could also be replicated to specific types of protests like riots, demonstrations, hunger strikes, etc. It is likely each form of protest responds to different mechanisms and that some of them do not disseminate at all.

7 Conclusions

After a mostly descriptive and exploratory analysis, it must be noted that a strong positive association exists between the protests that occur in a country i and the news of protests it receives from a country j. Though efforts must be made to strengthen the capacity to make causal statements, this is a good first step to explore the complexities of protests, especially at the macro level, which had not been analyzed in this manner before.

As for the apparent mechanisms as to which protests propagate internationally, they seem to change from country to country and especially depending on the timing. For a contemporaneous transmission, internet penetration is the most relevant instrument for most countries in the sample, though trade and Facebook friendships are also relevant to a smaller number. For a one-month transmission, news from a trading partner are associated with a higher level of protests a month later. Whereas news from both trade partners and bordering neighbors are associated with a higher level of protests two or more months later.

Other possible mechanisms might be acting in the international propagation of protests, more research is needed in this respect. Also, given the relevance and complexity of the international transmission of protests, a more thorough approach is needed to identify causal effects, machine learning techniques might help in this respect. This work paves the way for further research in the area.

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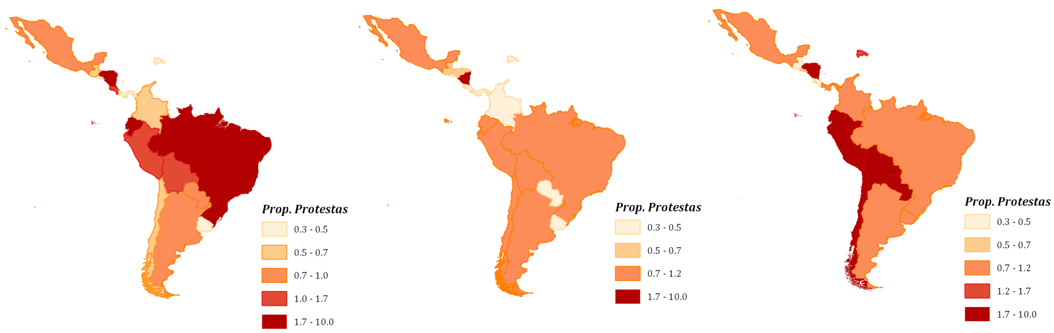
8 Annex

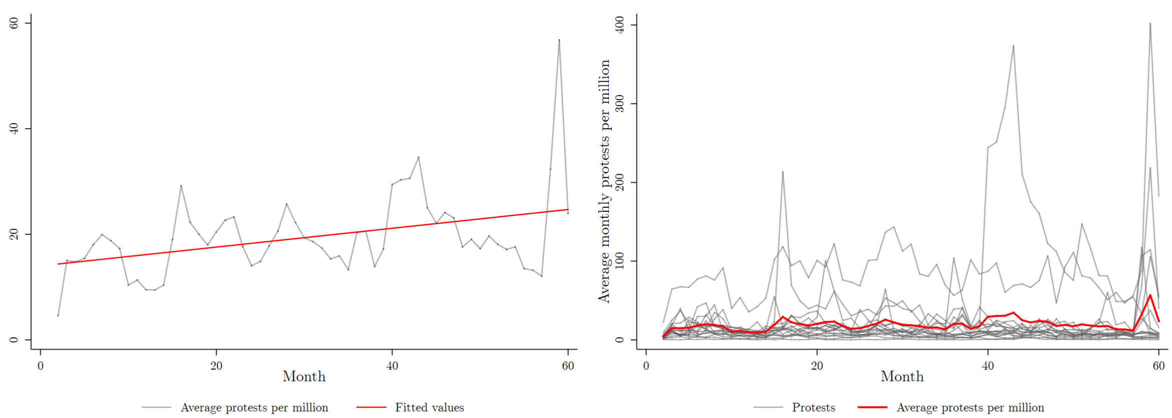
Map 1: Percentage of protests among all media covered events, for chosen Latin American Countries, august to October 2019

(a) 2019-08 **(b)** 2019-09 **(c)** 2019-10



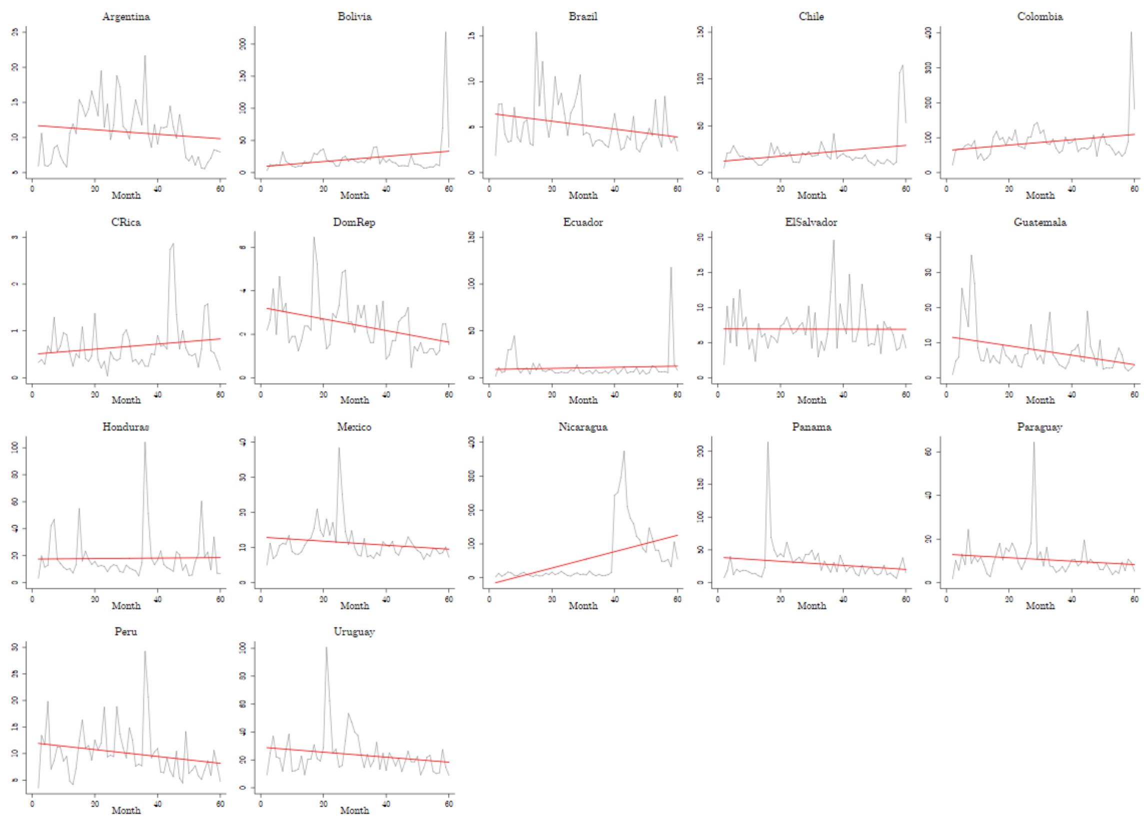
Source. Made by author on QGis software.

Figure 1: Average monthly protests produced across chosen Latin American countries, 2015-2019



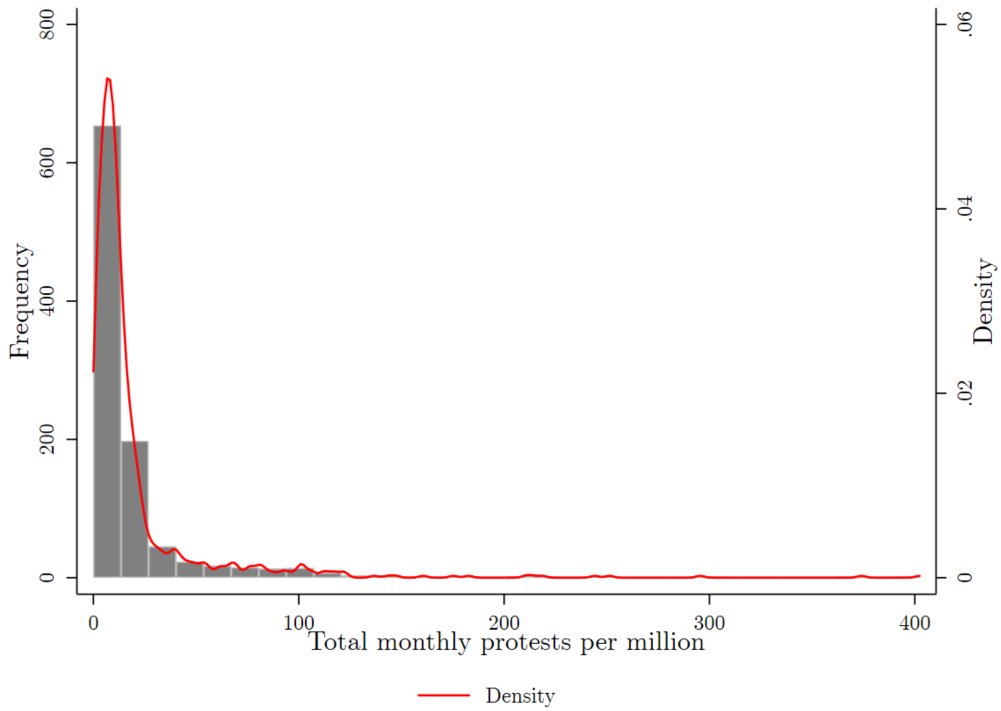
Source. Made by author.

Figure 2: Monthly protests produced by chosen Latin American countries, 2015-2019



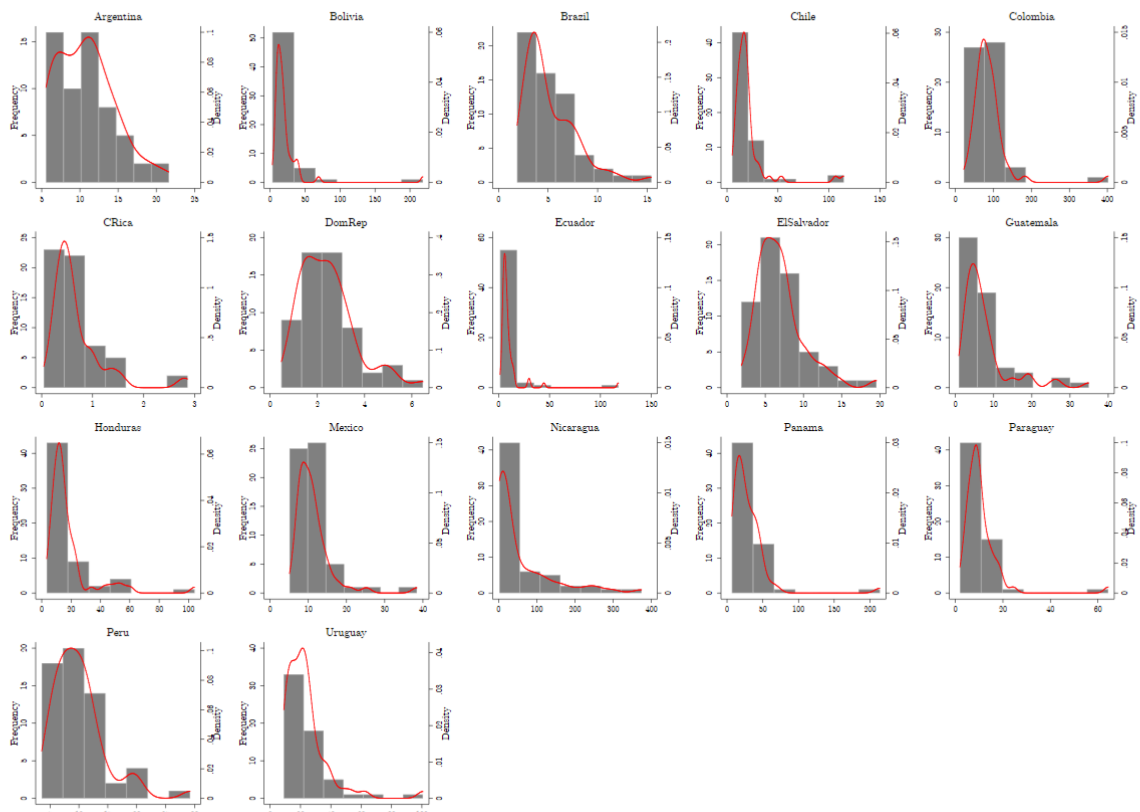
Source. Made by author.

Figure 3: Frequency distribution of monthly protests produced across chosen Latin American countries, 2015-2019



Source. Made by author.

Figure 4: Frequency distribution of monthly protests produced by chosen Latin American countries, 2015-2019



Source. Made by author.

Table 1: Correlations between countries for monthly protests per million inhabitants

Country	Argentina	Bolivia	Brazil	Chile	Colombia	Costa Rica	Dominican Republic	Ecuador	El Salvador	Guatemala	Honduras	Mexico	Nicaragua	Panama	Paraguay	Peru	Uruguay
Argentina	1.000																
Bolivia	0.037	1.000															
Brazil	0.282	-0.071	1.000														
Chile	-0.047	**0.834**	-0.097	1.000													
Colombia	0.091	**0.833**	0.096	**0.668**	1.000												
Costa Rica	-0.103	-0.125	-0.100	-0.149	-0.131	1.000											
Dominican Rep.	0.257	0.086	0.257	0.143	0.111	-0.106	1.000										
Ecuador	-0.139	0.252	-0.065	**0.580**	0.050	-0.034	0.105	1.000									
El Salvador	0.153	0.040	0.047	0.016	-0.031	0.028	0.125	-0.075	1.000								
Guatemala	-0.063	-0.137	-0.050	-0.079	-0.093	0.172	0.208	0.134	0.151	1.000							
Honduras	0.183	0.053	0.065	0.036	-0.151	-0.070	0.038	0.186	**0.404**	-0.002	1.000						
Mexico	0.251	0.004	0.267	-0.067	0.074	-0.077	**0.412**	-0.070	0.091	0.068	-0.106	1.000					
Nicaragua	-0.101	0.010	-0.240	-0.025	0.022	**0.350**	**-0.329**	-0.066	0.093	-0.070	-0.093	-0.167	1.000				
Panama	**0.340**	0.089	**0.330**	0.050	0.241	-0.033	0.227	-0.006	-0.063	-0.117	-0.073	0.250	-0.187	1.000			
Paraguay	**0.375**	0.037	**0.307**	0.042	0.181	0.101	0.187	0.073	0.039	0.118	-0.070	0.156	-0.071	0.214	1.000		
Peru	**0.417**	0.072	0.278	0.072	0.034	-0.177	0.249	0.017	**0.442**	0.121	**0.464**	0.094	-0.292	**0.313**	0.205	1.000	
Uruguay	**0.359**	-0.020	**0.448**	0.043	0.148	-0.185	0.082	-0.001	0.198	0.021	-0.042	0.187	-0.220	0.246	0.270	0.270	1.000

Source. Made by author.

Table 2: Correlations between countries in t and $t-1$ for monthly protests per million inhabitants

Countries in t	Monthly protests in $t-1$ by country																
	Argentina	Bolivia	Brazil	Chile	Colombia	Costa Rica	Dominican Republic	Ecuador	El Salvador	Guatemala	Honduras	Mexico	Nicaragua	Panama	Paraguay	Peru	Uruguay
Argentina		-0.019	0.246	-0.079	0.051	-0.129	0.33	-0.153	-0.067	-0.127	-0.106	**0.377**	-0.077	0.266	0.178	0.131	0.22
Bolivia	0.019		-0.106	**0.665**	0.119	-0.11	0.079	**0.839**	-0.142	-0.148	0.177	-0.004	-0.104	0.046	0.012	0.047	0.003
Brazil	0.225	-0.12		-0.202	-0.026	0.061	0.115	-0.007	-0.133	-0.13	-0.126	0.228	-0.298	**0.375**	**0.308**	0.122	0.125
Chile	-0.011	**0.395**	-0.078		0.219	-0.113	0.035	**0.586**	-0.144	-0.142	0.122	-0.11	-0.086	0.069	0.021	0.106	-0.006
Colombia	0.079	**0.489**	0.078	0.756		-0.093	0.161	0.777	-0.072	-0.116	0.061	0.096	-0.078	0.123	0.214	0.14	0.185
Costa Rica	-0.02	-0.188	-0.138	-0.157	-0.139		-0.059	-0.045	-0.055	0.111	0.035	-0.139	0.499	-0.151	0.107	-0.247	-0.094
Dominican Republic	0.251	-0.049	0.167	-0.014	-0.002	-0.012		0.017	0.019	0.062	0.083	**0.362**	-0.272	**0.527**	0.197	**0.361**	0.003
Ecuador	-0.214	-0.033	-0.1	-0.024	-0.103	-0.004	-0.042		-0.034	0.072	0.045	-0.098	-0.054	-0.158	-0.031	-0.107	-0.186
El Salvador	0.227	-0.076	-0.112	-0.143	-0.127	0.058	-0.002	-0.011		0.031	**0.398**	-0.095	0.023	-0.059	0.051	0.128	0.056
Guatemala	-0.145	-0.082	0.015	-0.072	-0.095	0.197	**0.324**	0.141	0.086		0.058	-0.002	-0.078	-0.066	0.178	0.009	0
Honduras	-0.049	-0.094	-0.101	-0.143	-0.197	-0.09	-0.123	-0.04	0.092	0.013		-0.185	-0.096	-0.061	-0.236	0.046	-0.193
Mexico	**0.339**	-0.083	0.277	-0.112	-0.003	-0.128	0.32	-0.024	-0.056	-0.033	-0.074		-0.2	0.278	0.172	0.055	0.176
Nicaragua	-0.094	-0.019	-0.239	0.006	-0.016	0.288	-0.273	0.018	0.189	-0.079	-0.093	-0.138		-0.157	-0.098	-0.276	-0.163
Panama	**0.413**	-0.007	0.64	-0.004	0.143	-0.131	0.158	0.013	-0.026	-0.093	0.235	0.235	-0.23		0.135	0.233	0.236
Paraguay	**0.314**	-0.027	0.191	-0.032	0.069	-0.018	**0.472**	0.024	-0.016	0.211	-0.053	0.274	-0.071	0.198		0.267	0.176
Peru	**0.375**	-0.057	0.162	-0.137	-0.083	-0.204	0.177	-0.099	0.047	-0.065	0.205	0.101	**-0.367**	0.161	0.027		0.199
Uruguay	**0.401**	-0.024	**0.351**	-0.09	0.069	0.009	0.122	-0.037	0.063	0.028	-0.023	0.193	-0.189	0.219	**0.361**	**0.313**	

Source. Made by author.

Table 3: Correlations between countries in t and $t-2$ for monthly protests per million inhabitants

Countries in t	Monthly protests in $t-2$ by country																
	Argentina	Bolivia	Brazil	Chile	Colombia	Costa Rica	Dominican Republic	Ecuador	El Salvador	Guatemala	Honduras	Mexico	Nicaragua	Panama	Paraguay	Peru	Uruguay
Argentina		0.204	0.131	0.018	0.264	-0.015	**0.341**	-0.169	0.004	-0.102	-0.174	**0.442**	-0.107	**0.35**	0.133	0.088	0.112
Bolivia	-0.083		0.044	0.053	-0.104	-0.033	-0.055	0.034	-0.14	-0.111	-0.03	-0.03	-0.096	-0.03	-0.057	-0.066	-0.136
Brazil	0.236	-0.064		-0.201	-0.014	-0.199	0.139	-0.17	-0.097	-0.05	-0.005	0.275	-0.265	0.046	-0.005	-0.089	0.122
Chile	-0.143	0.121	0.138		-0.106	0.078	-0.059	0.17	-0.135	-0.115	0.016	-0.065	-0.104	-0.065	-0.044	-0.025	-0.102
Colombia	0.102	0.262	-0.003	0.173		-0.029	0.06	0.175	-0.1	-0.171	-0.025	0.097	-0.114	0.011	0.056	0.014	-0.033
Costa Rica	-0.068	-0.167	-0.12	-0.138	-0.122		-0.041	-0.057	0.256	0.161	0.033	-0.071	0.61	-0.14	0.037	-0.072	-0.094
Dominican Republic	0.205	-0.105	0.41	-0.079	0.068	-0.083		-0.113	-0.034	-0.043	0.047	0.265	-0.214	**0.368**	-0.032	0.241	0.156
Ecuador	-0.298	-0.124	0.11	-0.07	-0.216	0.175	-0.045		-0.083	0.105	0.057	-0.085	-0.058	-0.132	-0.066	-0.061	-0.149
El Salvador	0.092	0.014	-0.01	0.05	0.017	0.119	-0.013	-0.129		0.042	-0.079	-0.006	0.103	-0.06	-0.03	0.089	-0.063
Guatemala	-0.216	-0.129	-0.071	-0.001	0.016	0.022	0.351	0.132	0.084		0.107	0.055	-0.006	0.022	0.072	0.035	-0.042
Honduras	-0.061	-0.136	-0.065	-0.052	-0.101	-0.088	-0.113	-0.103	-0.101	-0.001		-0.253	-0.101	-0.07	-0.161	-0.09	-0.1
Mexico	0.283	0.039	**0.375**	-0.029	0.097	-0.077	0.253	-0.095	0.047	-0.107	-0.044		-0.167	**0.384**	0.068	0.287	0.145
Nicaragua	-0.135	-0.091	-0.244	-0.064	0.055	0.232	-0.293	-0.069	0.056	-0.108	-0.078	-0.155		-0.156	-0.124	-0.229	-0.187
Panama	0.241	0.105	0.157	-0.093	0.084	-0.112	0.163	-0.045	-0.065	-0.159	-0.041	0.157	-0.233		0.06	0.044	0.041
Paraguay	0.114	0.091	0.172	-0.076	0.17	-0.035	**0.384**	-0.071	0.116	0.113	-0.04	**0.509**	-0.104	0.114		0.086	-0.02
Peru	0.273	0.053	0.104	-0.066	0.176	-0.212	0.138	-0.138	-0.007	-0.08	-0.05	**0.326**	-0.353	0.117	0.009		0.236
Uruguay	**0.375**	0.275	0.14	-0.027	0.2	0.012	0.279	-0.117	0.012	-0.061	-0.089	**0.352**	-0.21	0.145	**0.327**	0.021	

Source. Made by author.

Table 4: Monthly descriptive statistics by year and interest variable (P_{it}, M_{it}, $W_{ij} * M_{it}$)

Statistic	$Protests_{it}$	$News_{it}$	*News* $Major_{it}$	*News** $Border_{it}$	*News** $distance_{it}$	*News** $internet_{it}$	*News* ages* $15-34_{it}$	*News* ages* $15-64_{it}$	*News** $trade_{it}$	*News** $Facebook_{it}$
					2015					
Mean	14.11	85.24	30.60	34.76	47.91	27.91	9.62	36.88	25.71	3645272.00
Median	10.19	54.00	19.00	15.00	31.94	17.26	6.03	23.01	14.97	1482887.00
Standard Dev	15.57	95.78	36.85	46.00	53.87	33.82	10.87	41.49	31.07	7233419.00
Minimum	0.29	4.00	2.00	0.00	2.72	0.66	0.48	1.59	0.20	151116.00
Maximum	91.54	755.00	238.00	270.00	329.75	248.02	87.43	325.19	193.04	58200000.00
N	187	187	187	187	187	187	187	187	187	187
					2016					
Mean	18.88	106.76	41.02	38.73	44.87	37.58	11.71	46.73	27.96	3124579.00
Median	11.49	51.50	20.00	15.00	29.97	16.84	5.87	22.45	12.98	1625020.00
Standard Dev	26.26	132.13	62.04	57.98	42.62	50.73	14.33	58.20	39.28	4147836.00
Minimum	0.04	1.00	1.00	0.00	0.22	0.17	0.13	0.37	0.00	15715.00
Maximum	213.78	748.00	386.00	416.00	227.32	278.58	81.52	322.05	311.70	27700000.00
N	204	204	204	204	204	204	204	204	204	204
					2017					
Mean	18.46	84.88	32.64	32.66	43.55	29.30	9.39	36.87	22.74	3058452.00
Median	10.82	44.50	16.50	15.00	25.66	13.85	5.37	19.41	11.93	1417187.00
Standard Dev	24.37	94.74	41.63	49.85	51.11	36.92	10.33	41.41	30.28	4544472.00
Minimum	0.25	2.00	1.00	0.00	1.96	0.35	0.26	0.80	0.15	60752.00
Maximum	143.47	492.00	299.00	376.00	365.34	213.73	51.34	215.18	264.12	28500000.00
N	204	204	204	204	204	204	204	204	204	204
					2018					
Mean	24.06	114.72	65.40	33.41	88.27	27.73	13.27	49.29	31.36	8346226.00
Median	10.49	79.00	43.50	17.00	47.78	18.12	9.07	33.75	18.57	2226003.00
Standard Dev	48.20	110.71	76.40	44.15	119.89	29.70	12.84	47.79	33.03	26300000.00
Minimum	0.25	1.00	1.00	0.00	2.18	0.09	0.13	0.41	0.61	21868.00
Maximum	374.02	817.00	679.00	263.00	785.25	160.77	97.42	349.02	167.31	264000000.00
N	204	204	204	204	204	204	204	204	204	204
					2019					
Mean	21.73	105.55	43.11	38.71	62.50	33.25	11.81	45.90	29.23	3895605.00
Median	8.02	58.50	25.00	13.00	37.23	13.91	6.96	25.22	17.47	1517817.00
Standard Dev	42.01	159.02	64.40	90.02	96.21	61.47	17.14	69.42	43.72	6642980.00
Minimum	0.16	8.00	3.00	0.00	5.24	0.96	1.04	3.19	0.81	142395.00
Maximum	402.31	1146.00	459.00	743.00	914.45	448.15	129.64	498.94	325.26	44200000.00
N	204	204	204	204	204	204	204	204	204	204
					Total					
Mean	19.54	99.67	42.76	35.67	57.58	31.21	11.19	43.24	27.43	4427057.00
Median	10.10	58.00	23.00	14.00	34.22	15.88	6.81	24.73	15.16	1647691.00
Standard Dev	33.83	121.70	59.66	60.17	80.68	44.36	13.42	53.10	35.98	13000000.00
Minimum	0.04	1.00	1.00	0.00	0.22	0.09	0.13	0.37	0.00	15715.00
Maximum	402.31	1146.00	679.00	743.00	914.45	448.15	129.64	498.94	325.26	264000000.00
N	1003	1003	1003	1003	1003	1003	1003	1003	1003	1003

Source. Made by author.

Table 5: Monthly protests (per million inhab.) produced in country i by protests produced in country j and reported in i in the same month

News in i about protests produced in j	Monthly protests (per million)				
	Mean	**Median**	**Standad D**	**Minimum**	**Maximum**
1-16	9.23	6.57	9.53	0.04	54.35
16-24	16.06	9.23	34.89	0.20	295.55
24-35	27.63	8.67	57.56	0.25	374.02
35-44	17.86	10.05	27.69	0.22	210.66
44-58	15.52	8.44	21.01	0.35	111.14
58-76	19.48	9.83	27.12	0.16	182.67
76-108	16.13	10.25	18.74	0.47	121.64
108-153	18.27	11.01	21.64	0.53	106.63
153-221	26.24	12.47	35.49	0.37	218.55
221-more	27.92	11.54	48.88	2.50	402.31
Total	**19.54**	**10.10**	**33.83**	**0.04**	**402.31**

Source. Made by author.

Table 6: Correlations between monthly production of protests by country i and weighted news reports received from j in t.

Country i	News	Weighted by							
		Largest amount of reports from a single country	Border	Inverse distance	Average personal access to internet	Average portion of ages 15-34	Average portion of ages 15-64	Bilateral trade	Social Connectedness Index
Argentina	0.171	0.133	0.146	0.111	0.167	0.17	0.172	0.184	**0.275**
Bolivia	0.367	0.181	0.225	0.332	**0.477**	0.348	0.378	0.408	0.431
Brazil	-0.042	-0.099	0.151	-0.013	0.023	-0.051	-0.04	**0.166**	0.107
Chile	0.215	0.274	0.159	0.077	0.224	0.215	0.215	0.262	**0.472**
Colombia	0.268	0.104	0.106	0.172	**0.298**	0.258	0.268	0.262	0.104
Costa Rica	0.495	0.52	0.559	0.563	0.335	0.504	0.493	**0.572**	0.487
Dominican Rep.	0.172	0.13	-	0.009	**0.294**	0.15	0.181	0.119	-0.186
Ecuador	0.358	0.246	0.093	0.185	**0.467**	0.336	0.362	0.383	0.267
El Salvador	0.296	0.285	0.317	**0.336**	0.294	0.299	0.293	0.331	0.306
Guatemala	-0.171	-0.16	0.018	-0.146	-0.141	**-0.172**	-0.171	-0.139	0.033
Honduras	0.111	-0.026	-0.055	-0.055	**0.249**	0.096	0.113	-0.034	0.161
Mexico	0.188	0.105	0.124	0.071	**0.256**	0.174	0.189	0.224	-0.096
Nicaragua	0.189	-0.012	0.078	0.071	**0.284**	0.167	0.198	0.016	0.157
Panama	-0.045	-0.14	**0.226**	-0.129	0.075	-0.058	-0.037	-0.157	-0.017
Paraguay	0.093	0.057	0.115	**0.127**	0.124	0.087	0.097	0.112	0.08
Peru	-0.008	**-0.132**	0.054	-0.011	0.06	-0.018	-0.006	0.043	-0.071
Uruguay	0.031	0.048	**0.255**	0.132	0.096	0.022	0.035	0.245	0.141
Average	0.158	0.089	0.161	0.108	**0.211**	0.149	0.161	0.176	0.156

Source. Made by author.

Table 7: Correlations between monthly production of protests by country i and weighted news reports received from j in $t-1$.

Country i	**News**	**Weighted by**							
		Largest amount of reports from a single country	**Border**	**Inverse distance**	**Average personal access to internet**	**Average portion of ages 15-34**	**Average portion of ages 15-64**	**Bilateral trade**	**Social Connectedness Index**
Argentina	0.101	0.089	0.059	0.033	0.102	0.102	0.103	0.101	**0.185**
Bolivia	0.224	0.138	0.118	0.237	**0.305**	0.21	0.224	0.295	0.297
Brazil	-0.172	-0.17	-0.005	-0.123	-0.108	**-0.179**	-0.169	-0.021	-0.039
Chile	0.064	0.185	0.077	-0.025	0.091	0.06	0.064	**0.236**	0.157
Colombia	0.496	0.357	0.51	0.591	0.546	0.483	0.497	**0.677**	0.384
Costa Rica	0.455	0.515	0.527	0.531	0.298	0.463	0.453	**0.54**	0.518
Dominican Rep.	0.074	0.062	-	0.008	0.119	0.069	0.074	0.119	**-0.173**
Ecuador	-0.073	**-0.1**	-0.009	-0.066	-0.034	-0.075	-0.071	-0.033	-0.031
El Salvador	0.112	0.155	0.167	0.17	0.061	0.118	0.11	**0.193**	0.047
Guatemala	-0.102	-0.138	0.066	-0.134	-0.037	-0.104	-0.098	**-0.138**	0.04
Honduras	-0.009	-0.043	-0.028	-0.05	0.048	-0.011	-0.013	-0.018	**0.075**
Mexico	0.123	0.024	0.038	-0.006	**0.199**	0.108	0.126	0.166	-0.136
Nicaragua	0.1	-0.084	0.015	0.006	**0.183**	0.081	0.108	-0.032	0.113
Panama	0.015	-0.066	0.056	-0.154	0.178	-0.002	0.026	**-0.18**	-0.071
Paraguay	0.051	-0.026	0.073	0.055	0.059	0.048	0.047	0.117	**0.21**
Peru	-0.153	**-0.169**	-0.104	-0.166	-0.082	-0.164	-0.151	-0.107	-0.118
Uruguay	0.025	0.055	**0.37**	0.126	0.065	0.019	0.028	0.298	0.191
Average	0.078	0.046	0.121	0.061	0.117	0.072	0.080	0.130	0.097

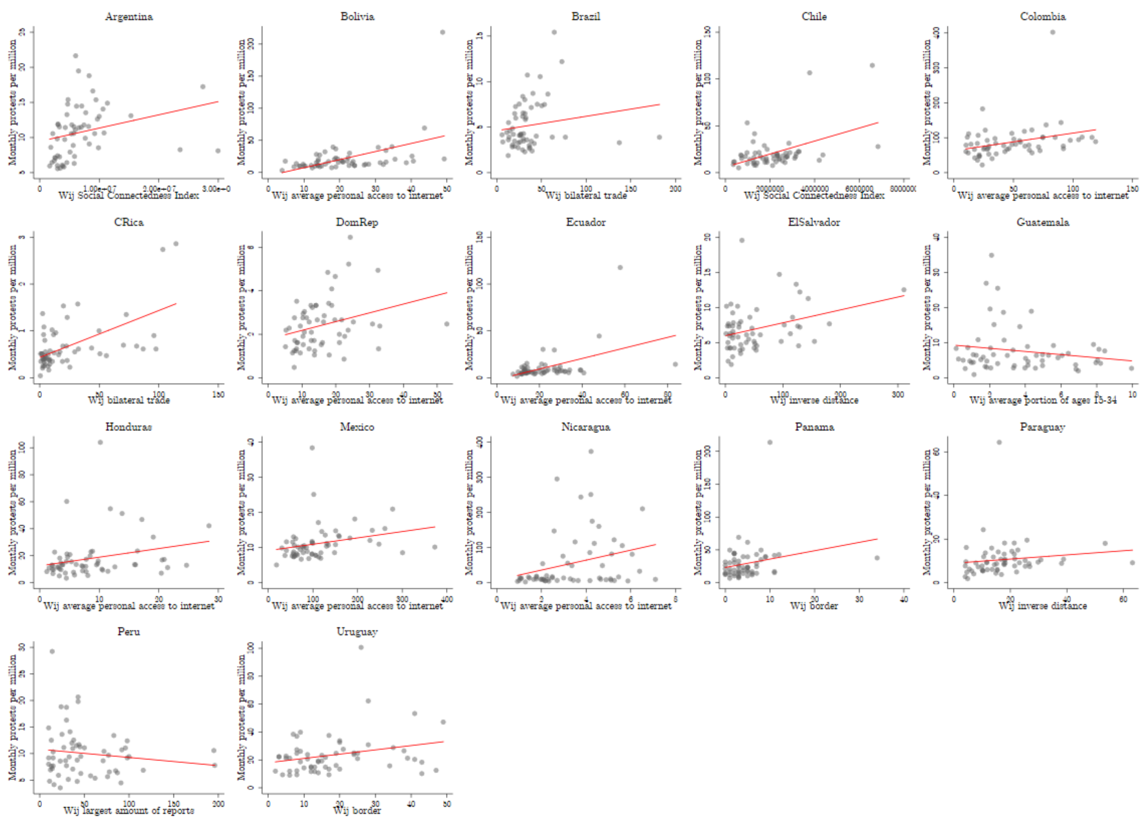
Source. Made by author.

Table 8: Correlations between monthly production of protests by country i and weighted news reports received from j in $t-2$.

Country i	**News**	**Weighted by**							
		Largest amount of reports from a single country	**Border**	**Inverse distance**	**Average personal access to internet**	**Average portion of ages 15-34**	**Average portion of ages 15-64**	**Bilateral trade**	**Social Connectedness Index**
Argentina	0.186	0.134	0.142	0.152	**0.19**	0.183	0.186	0.129	0.188
Bolivia	-0.052	**-0.082**	0.031	0	-0.006	-0.057	-0.048	0.035	-0.025
Brazil	-0.108	-0.108	**0.159**	-0.095	-0.029	-0.12	-0.107	0.157	-0.041
Chile	-0.193	-0.014	-0.161	**-0.205**	-0.128	-0.198	-0.185	-0.023	-0.202
Colombia	0.07	0.012	0.09	0.068	0.114	0.062	0.071	**0.159**	-0.011
Costa Rica	0.41	0.446	0.437	0.447	0.277	0.418	0.406	**0.465**	0.377
Dominican Rep.	0.232	0.253	-	0.088	**0.308**	0.215	0.243	0.127	-0.101
Ecuador	-0.045	**-0.09**	0.087	-0.015	-0.026	-0.043	-0.043	0	-0.047
El Salvador	0.173	**0.226**	0.024	0.17	0.121	0.173	0.172	0.178	0.104
Guatemala	-0.068	**-0.098**	-0.046	-0.052	-0.052	-0.066	-0.066	-0.044	-0.05
Honduras	-0.115	-0.075	-0.042	-0.069	**-0.123**	-0.108	-0.121	-0.04	-0.035
Mexico	0.191	0.131	-0.092	-0.009	0.267	0.171	0.199	**0.263**	-0.118
Nicaragua	0.047	-0.129	-0.02	-0.038	**0.13**	0.028	0.055	-0.076	0.065
Panama	-0.184	-0.226	0.029	-0.236	-0.078	-0.193	-0.179	**-0.243**	-0.164
Paraguay	0.078	0.07	0.023	0.047	**0.107**	0.073	0.078	0.01	0.043
Peru	-0.061	**-0.128**	-0.015	-0.101	0.034	-0.077	-0.055	-0.042	0.004
Uruguay	-0.048	-0.069	0.14	0.115	0.023	-0.056	-0.046	**0.217**	0.17
Average	0.030	0.015	0.049	0.016	0.066	0.024	0.033	0.075	0.009

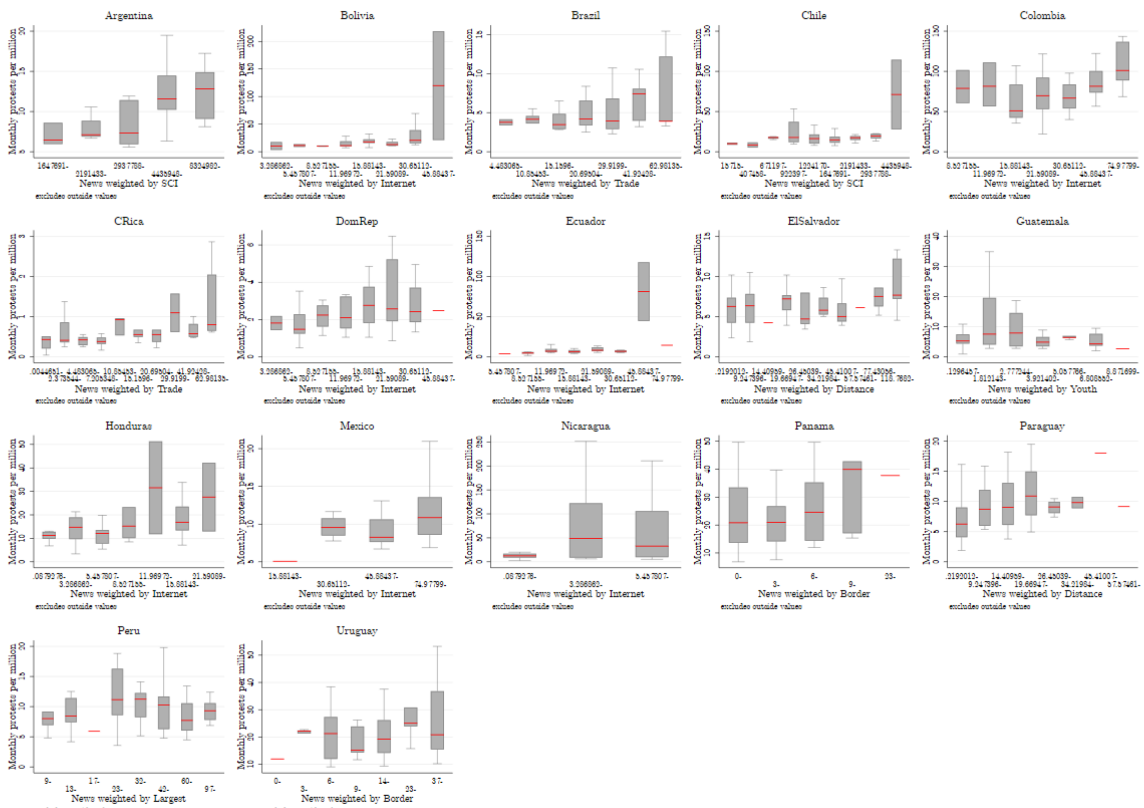
Source. Made by author.

Figure 5: Monthly protests produced in country i at time t by most important transmission mechanism for news about protests produced in j at time t, 2015-2019



Source. Made by author.

Figure 6: Monthly protests produced in country i at time t by most important transmission mechanism for news about protests produced in j at time t in equally sized groups, 2015-2019



Source. Made by author.

Matrix 1: Binary contiguity matrix for border countries

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	GTM	HDN	MEX	NIC	PAN	PRY	PER	URY
ARG	0	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	1
BOL	1	0	1	1	0	0	0	0	0	0	0	0	0	0	1	1	0
BRA	1	1	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1
CHL	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
COL	0	0	1	0	0	0	0	1	0	0	0	0	0	1	0	1	0
CRI	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
DOM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ECU	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0
SLV	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
GTM	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0
HDN	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	0
MEX	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
NIC	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0
PAN	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
PRY	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PER	0	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0
URY	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Source. Made by author.

Matrix 2: Contiguity matrix for the inverse distance between countries' centroids

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	GTM	HDN	MEX	NIC	PAN	PRY	PER	URY
ARG	0	0.484	0.335	1.615	0.226	0.185	0.166	0.249	0.167	0.160	0.167	0.131	0.174	0.196	0.668	0.328	1.122
BOL	0.484	0	0.707	0.411	0.406	0.274	0.251	0.437	0.233	0.219	0.236	0.164	0.252	0.306	1.025	0.744	0.504
BRA	0.335	0.707	0	0.285	0.364	0.242	0.263	0.331	0.209	0.198	0.215	0.151	0.228	0.272	0.671	0.427	0.407
CHL	1.615	0.411	0.285	0	0.216	0.183	0.159	0.244	0.167	0.160	0.165	0.132	0.173	0.192	0.490	0.313	0.665
COL	0.226	0.406	0.364	0.216	0	0.715	0.594	1.156	0.488	0.435	0.522	0.259	0.608	1.076	0.294	0.689	0.225
CRI	0.185	0.274	0.242	0.183	0.715	0	0.563	0.716	1.519	1.085	1.672	0.402	3.025	2.095	0.216	0.420	0.179
DOM	0.166	0.251	0.263	0.159	0.594	0.563	0	0.413	0.489	0.467	0.563	0.297	0.590	0.646	0.207	0.319	0.169
ECU	0.249	0.437	0.331	0.244	1.156	0.716	0.413	0	0.497	0.438	0.501	0.263	0.580	0.902	0.306	1.016	0.238
SLV	0.167	0.233	0.209	0.167	0.488	1.519	0.489	0.497	0	3.700	3.698	0.547	2.343	0.894	0.190	0.334	0.161
GTM	0.160	0.219	0.198	0.160	0.435	1.085	0.467	0.438	3.700	0	2.420	0.638	1.525	0.730	0.181	0.306	0.154
HDN	0.167	0.236	0.215	0.165	0.522	1.672	0.563	0.501	3.698	2.420	0	0.513	3.597	1.004	0.192	0.336	0.161
MEX	0.131	0.164	0.151	0.132	0.259	0.402	0.297	0.263	0.547	0.638	0.513	0	0.451	0.341	0.141	0.209	0.125
NIC	0.174	0.252	0.228	0.173	0.608	3.025	0.590	0.580	2.343	1.525	3.597	0.451	0	1.385	0.203	0.370	0.169
PAN	0.196	0.306	0.272	0.192	1.076	2.095	0.646	0.902	0.894	0.730	1.004	0.341	1.385	0	0.236	0.487	0.191
PRY	0.668	1.025	0.671	0.490	0.294	0.216	0.207	0.306	0.190	0.181	0.192	0.141	0.203	0.236	0	0.433	0.921
PER	0.328	0.744	0.427	0.313	0.689	0.420	0.319	1.016	0.334	0.306	0.336	0.209	0.370	0.487	0.433	0	0.310
URY	1.122	0.504	0.407	0.665	0.225	0.179	0.169	0.238	0.161	0.154	0.161	0.125	0.169	0.191	0.921	0.310	0

Source. Made by author using ArcGis.

Matrix 3: Contiguity matrix for the probability two individuals connect directly

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	GTM	HDN	MEX	NIC	PAN	PRY	PER	URY
ARG	0	0.282	0.442	0.575	0.418	0.467	0.440	0.380	0.212	0.304	0.209	0.429	0.171	0.386	0.389	0.320	0.472
BOL	0.282	0	0.247	0.321	0.233	0.261	0.246	0.212	0.119	0.170	0.117	0.239	0.095	0.216	0.217	0.179	0.264
BRA	0.442	0.247	0	0.503	0.366	0.409	0.385	0.332	0.186	0.266	0.183	0.375	0.150	0.338	0.341	0.280	0.413
CHL	0.575	0.321	0.503	0	0.475	0.531	0.500	0.432	0.241	0.346	0.238	0.487	0.194	0.439	0.442	0.364	0.537
COL	0.418	0.233	0.366	0.475	0	0.386	0.364	0.314	0.176	0.251	0.173	0.354	0.141	0.319	0.322	0.265	0.390
CRI	0.467	0.261	0.409	0.531	0.386	0	0.406	0.351	0.196	0.281	0.193	0.396	0.158	0.357	0.359	0.296	0.436
DOM	0.440	0.246	0.385	0.500	0.364	0.406	0	0.331	0.185	0.265	0.182	0.373	0.149	0.336	0.339	0.279	0.411
ECU	0.380	0.212	0.332	0.432	0.314	0.351	0.331	0	0.160	0.229	0.157	0.322	0.128	0.290	0.292	0.240	0.355
SLV	0.212	0.119	0.186	0.241	0.176	0.196	0.185	0.160	0	0.128	0.088	0.180	0.072	0.162	0.164	0.134	0.198
GTM	0.304	0.170	0.266	0.346	0.251	0.281	0.265	0.229	0.128	0	0.126	0.258	0.103	0.232	0.234	0.193	0.284
HDN	0.209	0.117	0.183	0.238	0.173	0.193	0.182	0.157	0.088	0.126	0	0.177	0.071	0.160	0.161	0.132	0.195
MEX	0.429	0.239	0.375	0.487	0.354	0.396	0.373	0.322	0.180	0.258	0.177	0	0.145	0.328	0.330	0.271	0.400
NIC	0.171	0.095	0.150	0.194	0.141	0.158	0.149	0.128	0.072	0.103	0.071	0.145	0	0.131	0.132	0.108	0.160
PAN	0.386	0.216	0.338	0.439	0.319	0.357	0.336	0.290	0.162	0.232	0.160	0.328	0.131	0	0.298	0.245	0.361
PRY	0.389	0.217	0.341	0.442	0.322	0.359	0.339	0.292	0.164	0.234	0.161	0.330	0.132	0.298	0	0.246	0.364
PER	0.320	0.179	0.280	0.364	0.265	0.296	0.279	0.240	0.134	0.193	0.132	0.271	0.108	0.245	0.246	0	0.299
URY	0.472	0.264	0.413	0.537	0.390	0.436	0.411	0.355	0.198	0.284	0.195	0.400	0.160	0.361	0.364	0.299	0

Source. Made by author using data from the United Nations specialized agency for information and communication technologies.

Matrix 4: Contiguity matrix for probability two young (15-34) individuals directly

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	GTM	HDN	MEX	NIC	PAN	PRY	PER	URY
ARG	0	0.108	0.103	0.096	0.106	0.103	0.106	0.106	0.110	0.116	0.117	0.104	0.112	0.099	0.115	0.103	0.090
BOL	0.108	0	0.115	0.107	0.118	0.115	0.118	0.119	0.123	0.130	0.131	0.116	0.125	0.110	0.128	0.115	0.100
BRA	0.103	0.115	0	0.102	0.112	0.110	0.113	0.113	0.117	0.123	0.125	0.111	0.119	0.105	0.122	0.109	0.095
CHL	0.096	0.107	0.102	0	0.105	0.102	0.105	0.106	0.109	0.115	0.117	0.103	0.112	0.098	0.114	0.102	0.089
COL	0.106	0.118	0.112	0.105	0	0.113	0.116	0.116	0.120	0.127	0.128	0.114	0.123	0.108	0.126	0.113	0.098
CRI	0.103	0.115	0.110	0.102	0.113	0	0.113	0.113	0.117	0.124	0.125	0.111	0.120	0.105	0.122	0.110	0.096
DOM	0.106	0.118	0.113	0.105	0.116	0.113	0	0.117	0.121	0.128	0.129	0.114	0.123	0.109	0.126	0.113	0.098
ECU	0.106	0.119	0.113	0.106	0.116	0.113	0.117	0	0.121	0.128	0.129	0.114	0.124	0.109	0.126	0.113	0.099
SLV	0.110	0.123	0.117	0.109	0.120	0.117	0.121	0.121	0	0.132	0.133	0.118	0.128	0.112	0.131	0.117	0.102
GTM	0.116	0.130	0.123	0.115	0.127	0.124	0.128	0.128	0.132	0	0.141	0.125	0.135	0.119	0.138	0.124	0.108
HDN	0.117	0.131	0.125	0.117	0.128	0.125	0.129	0.129	0.133	0.141	0	0.126	0.136	0.120	0.139	0.125	0.109
MEX	0.104	0.116	0.111	0.103	0.114	0.111	0.114	0.114	0.118	0.125	0.126	0	0.121	0.107	0.124	0.111	0.097
NIC	0.112	0.125	0.119	0.112	0.123	0.120	0.123	0.124	0.128	0.135	0.136	0.121	0	0.115	0.134	0.120	0.104
PAN	0.099	0.110	0.105	0.098	0.108	0.105	0.109	0.109	0.112	0.119	0.120	0.107	0.115	0	0.117	0.105	0.092
PRY	0.115	0.128	0.122	0.114	0.126	0.122	0.126	0.126	0.131	0.138	0.139	0.124	0.134	0.117	0	0.122	0.106
PER	0.103	0.115	0.109	0.102	0.113	0.110	0.113	0.113	0.117	0.124	0.125	0.111	0.120	0.105	0.122	0	0.096
URY	0.090	0.100	0.095	0.089	0.098	0.096	0.098	0.099	0.102	0.108	0.109	0.097	0.104	0.092	0.106	0.096	0

Source. Made by author using World Development Indicators by the World Bank.

Matrix 5: Contiguity matrix for probability two young (15-64) individuals directly

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	GTM	HDN	MEX	NIC	PAN	PRY	PER	URY
ARG	0	0.394	0.447	0.441	0.443	0.437	0.416	0.414	0.413	0.386	0.404	0.423	0.413	0.415	0.410	0.421	0.414
BOL	0.394	0	0.428	0.422	0.425	0.419	0.398	0.397	0.395	0.370	0.387	0.406	0.395	0.398	0.393	0.403	0.396
BRA	0.447	0.428	0	0.479	0.482	0.475	0.452	0.451	0.448	0.420	0.439	0.460	0.449	0.451	0.446	0.457	0.450
CHL	0.441	0.422	0.479	0	0.475	0.469	0.446	0.445	0.443	0.414	0.433	0.454	0.443	0.445	0.440	0.451	0.444
COL	0.443	0.425	0.482	0.475	0	0.472	0.448	0.447	0.445	0.417	0.436	0.456	0.445	0.448	0.442	0.454	0.446
CRI	0.437	0.419	0.475	0.469	0.472	0	0.442	0.441	0.439	0.411	0.430	0.450	0.439	0.442	0.437	0.448	0.440
DOM	0.416	0.398	0.452	0.446	0.448	0.442	0	0.419	0.417	0.391	0.409	0.428	0.417	0.420	0.415	0.426	0.418
ECU	0.414	0.397	0.451	0.445	0.447	0.441	0.419	0	0.416	0.390	0.408	0.427	0.416	0.419	0.414	0.424	0.417
SLV	0.413	0.395	0.448	0.443	0.445	0.439	0.417	0.416	0	0.388	0.406	0.425	0.414	0.417	0.412	0.422	0.415
GTM	0.386	0.370	0.420	0.414	0.417	0.411	0.391	0.390	0.388	0	0.380	0.398	0.388	0.390	0.386	0.395	0.389
HDN	0.404	0.387	0.439	0.433	0.436	0.430	0.409	0.408	0.406	0.380	0	0.416	0.406	0.408	0.403	0.414	0.407
MEX	0.423	0.406	0.460	0.454	0.456	0.450	0.428	0.427	0.425	0.398	0.416	0	0.425	0.427	0.423	0.433	0.426
NIC	0.413	0.395	0.449	0.443	0.445	0.439	0.417	0.416	0.414	0.388	0.406	0.425	0	0.417	0.412	0.423	0.415
PAN	0.415	0.398	0.451	0.445	0.448	0.442	0.420	0.419	0.417	0.390	0.408	0.427	0.417	0	0.414	0.425	0.418
PRY	0.410	0.393	0.446	0.440	0.442	0.437	0.415	0.414	0.412	0.386	0.403	0.423	0.412	0.414	0	0.420	0.413
PER	0.421	0.403	0.457	0.451	0.454	0.448	0.426	0.424	0.422	0.395	0.414	0.433	0.423	0.425	0.420	0	0.424
URY	0.414	0.396	0.450	0.444	0.446	0.440	0.418	0.417	0.415	0.389	0.407	0.426	0.415	0.418	0.413	0.424	0

Source. Made by author using World Development Indicators by the World Bank.

Matrix 6: Contiguity matrix commerce openness between two countries

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	GTM	HDN	MEX	NIC	PAN	PRY	PER	URY
ARG	0	0.304	0.756	0.412	0.103	0.009	0.015	0.064	0.001	0.004	0.003	0.117	0.001	0.011	0.345	0.208	0.223
BOL	0.451	0	0.171	0.157	0.182	0.003	0.002	0.130	0.002	0.002	0.001	0.022	0.003	0.010	0.150	0.375	0.058
BRA	0.823	0.157	0	0.385	0.200	0.018	0.035	0.047	0.006	0.016	0.006	0.293	0.004	0.094	0.187	0.175	0.190
CHL	0.452	0.127	0.395	0	0.291	0.056	0.022	0.459	0.027	0.060	0.013	0.222	0.010	0.056	0.232	0.568	0.076
COL	0.102	0.150	0.176	0.305	0	0.083	0.089	0.599	0.030	0.097	0.035	0.342	0.027	0.922	0.013	0.348	0.034
CRI	0.019	0.003	0.018	0.081	0.094	0	0.189	0.041	0.637	0.726	0.597	0.105	0.819	0.675	0.011	0.028	0.030
DOM	0.022	0.003	0.037	0.024	0.104	0.178	0	0.048	0.102	0.122	0.111	0.071	0.047	0.080	0.007	0.033	0.043
ECU	0.082	0.173	0.046	0.487	0.568	0.044	0.048	0	0.087	0.055	0.064	0.060	0.121	1.679	0.044	0.516	0.051
SLV	0.007	0.003	0.008	0.026	0.040	0.655	0.102	0.059	0	2.044	2.721	0.069	1.749	0.448	0.003	0.024	0.063
GTM	0.020	0.004	0.015	0.061	0.123	0.774	0.117	0.065	2.266	0	1.375	0.203	0.754	0.593	0.006	0.045	0.072
HDN	0.012	0.003	0.008	0.017	0.044	0.464	0.056	0.056	1.424	0.853	0	0.057	0.763	0.068	0.014	0.029	0.065
MEX	0.093	0.016	0.313	0.198	0.315	0.099	0.058	0.058	0.080	0.191	0.095	0	0.095	0.103	0.014	0.134	0.042
NIC	0.010	0.004	0.008	0.015	0.021	0.862	0.039	0.062	1.562	0.635	1.751	0.084	0	0.095	0.009	0.015	0.021
PAN	0.029	0.036	0.022	0.119	0.353	0.955	0.377	0.238	0.517	0.469	0.481	0.087	0.593	0	0.083	0.140	0.134
PRY	0.705	0.133	0.272	0.311	0.014	0.012	0.004	0.034	0.004	0.010	0.002	0.013	0.002	0.106	0	0.056	0.397
PER	0.178	0.427	0.175	0.487	0.387	0.030	0.033	0.651	0.040	0.047	0.028	0.156	0.014	0.185	0.064	0	0.071
URY	0.264	0.075	0.141	0.064	0.016	0.020	0.005	0.022	0.001	0.007	0.002	0.026	0.002	0.033	0.237	0.051	0

Source. Made by author using monthly data from Trade Map.

Matrix 7: Contiguity matrix social connectedness index for Facebook users

	ARG	BOL	BRA	CHL	COL	CRI	DOM	ECU	SLV	GTM	HDN	MEX	NIC	PAN	PRY	PER	URY
ARG	0	49,314	4,879	24,498	11,374	9,737	11,730	10,522	6,624	8,197	7,381	9,222	9,421	15,922	271,970	7,316	80,801
BOL	49,314	0	10,358	56,560	11,132	9,134	7,841	15,264	20,331	15,715	10,470	18,829	9,161	38,455	45,466	13,571	9,036
BRA	4,879	10,358	0	3,234	3,790	3,008	6,519	3,130	2,251	2,892	1,963	3,408	3,765	3,254	32,523	2,311	12,987
CHL	24,498	56,560	3,234	0	35,619	10,322	37,287	24,931	4,254	5,637	6,094	5,793	20,365	39,120	25,077	5,501	20,109
COL	11,374	11,132	3,790	35,619	0	18,534	23,384	49,885	11,116	16,526	10,178	19,346	72,856	28,426	16,494	11,966	9,007
CRI	9,737	9,134	3,008	10,322	18,534	0	24,801	14,349	38,923	67,953	12,713	1,256,348	180,483	11,216	16,882	61,826	9,993
DOM	11,730	7,841	6,519	37,287	23,384	24,801	0	16,939	11,551	24,859	9,338	27,725	74,957	10,686	19,290	15,123	20,421
ECU	10,522	15,264	3,130	24,931	49,885	14,349	16,939	0	12,429	18,843	9,938	19,975	23,447	28,998	20,702	13,021	8,731
SLV	6,624	20,331	2,251	4,254	11,116	38,923	11,551	12,429	0	136,863	21,868	86,493	18,878	9,751	23,014	104,795	5,043
GTM	8,197	15,715	2,892	5,637	16,526	67,953	24,860	18,843	136,863	0	25,605	205,640	44,226	13,173	27,512	188,962	6,904
HDN	7,381	10,470	1,963	6,094	10,178	12,713	9,338	9,938	21,868	25,605	0	17,647	8,650	9,710	14,131	17,397	5,919
MEX	9,222	18,829	3,408	5,793	19,346	1,256,348	27,725	19,975	86,493	205,640	17,647	0	378,790	15,171	29,502	113,394	7,020
NIC	9,421	9,161	3,765	20,365	72,856	180,483	74,957	23,447	18,878	44,226	8,650	378,790	0	18,085	17,435	43,162	12,174
PAN	15,922	38,455	3,254	39,120	28,426	11,216	10,686	28,998	9,751	13,173	9,710	15,171	18,085	0	28,162	9,468	9,699
PRY	271,970	45,466	32,523	25,077	16,494	16,882	19,290	20,702	23,014	27,512	14,131	29,502	17,435	28,162	0	24,111	57,641
PER	7,316	13,571	2,311	5,501	11,966	61,826	15,123	13,021	104,795	188,962	17,397	113,394	43,162	9,468	24,111	0	6,673
URY	80,801	9,036	12,987	20,109	9,007	9,993	20,421	8,731	5,043	6,904	5,919	7,020	12,174	9,699	57,641	6,672	0

Source. Made by author using Social Connectedness Index data authorized by Facebook Data Analysis team.