Social Network Response to Social Unrest: Evidence from Mobile Phone Metadata in Haiti

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Abstract

We examine a period of social unrest in Haiti to understand how social networks respond to social unrest. To do this, we construct communication networks using mobile phone metadata from a major mobile network operator in Haiti and a detailed georeferenced timeline of protests, roadblocks, rock throwing, tire burning, and shootings. Episodes of severe unrest are geographically isolated and persist for a matter of days. Moreover, these events vary in their degree of coordination, and therefore predictability. We use the unpredictable events to estimate how call behavior responds from day-to-day. We find that contacts and calls decrease, but duration spent talking increases.

Keywords: Social Networks, Social Unrest, Digital Trace Data

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1 Introduction

Social and political movements, including protests and civil unrest, have always leveraged social networks in order to motivate and mobilize individuals (Campbell, 2013). As a particularly potent example, the pro-democracy protests of the Arab Spring erupted as online social media mobilized social networks into political action (Steinert-Threlkeld et al., 2015). But social networks are not a fixed form of social infrastructure; they evolve in times of stress or sudden change as incentives shift for individuals to connect and communicate with links new and old. In this paper, we study how communication networks respond to – rather than mobilize – acute civil unrest. Rather than focusing on communication among protesters and organizers, we aim to characterize a broader network that includes bystanders whose daily lives are disrupted by and who face greater uncertainty and risk to life and property as a direct result of localized unrest. This broader inquiry evaluates how such bystanders tap their networks to cope with these shocks.

One of the oft-cited benefits of Information and Communication Technology (ICT) for vulnerable populations is the added resilience that can come from better and more timely information, especially in advance of or immediately after shocks of different kinds. Many such applications use one-way SMS blasts to broadcast information to passive recipients as would-be beneficiaries (Azid et al., 2015). Others engage individuals more actively as creators of specific information through crowd-sourcing platforms (See, 2019). Still others harness individuals' movements or activities as relayed by their mobile devices or social media accounts as real-time signals of on-the-ground realities (Sakaki et al., 2010). While the analysis in this paper also showcases the potential value of ICT platforms to people coping with and responding to unexpected shocks, our objective is yet more specific: We aim to understand how those in close proximity to localized unrest use ICT-mediated social networks to cope with these shocks.

A few prior studies similarly study how social networks respond to major shocks. Jia et al. (2021) assess mobile communication patterns in the wake of the 2013 Ya'an earthquake in China, paying special attention to how common friends affect the dynamics of responses within families. Blumenstock et al. (2016) also leverage an earthquake, in Rwanda, and document the flow of assistance into affected areas through mobile communication networks in the form of airtime transfers.[1] These studies, like most others in this literature, focus on major covariate shocks that unexpected affect entire populations. While these can be devastating and costly shocks to be sure, they are blunt, one-off events that provide little variation with which to identify social network responses. For that, more frequent and localized shocks are more useful. One working paper uses this kind of variation (Blumenstock et al., 2020), but focuses on firms' location decision as shaped by violence in Afghanistan. Similarly, we leverage acute and spatially isolated spells of social unrest in Haiti to understand how uncertainty of social unrest drives ICT-mediated communication. That is, we estimate the impact of these episodes of social unrest on communication networks. Additionally, we work to understand what types of relationships are tapped in these situations. Do those who face unrest in their neighborhoods use this communication network more or less than their peers? Do people tend to communicate with a more diverse group, or simply more often with those that they know well?

Starting in 2018, Haiti faced a period of social unrest in response to reports of government corruption and embezzlement of loans from Venezuela's PetroCaribe program.[2] This period included mass demonstrations, roadblocks, and even forced the cancellation of Carnival events in both 2019 and 2020. We propose to examine this period of social unrest, leveraging acute and spatially-isolated unrest shocks as exogenous shocks to the value of mobile communication. In particular, we zoom in on the months of January and February in Port-Au-Prince, a period during which social unrest escalated. As a proxy for social networks we use mobile phone metadata from a large telecommunications provider in Haiti to construct mobile communications networks. Treating these mobile communication networks as the measure of social networks yields census-like networks without the prohibitive expense of in-person surveys. Moreover, the fine grained temporal nature of these communication networks yields the possibility to look at detailed short run changes in network usage in response to shocks. We aggregate network activity to a daily

[1]Bennett et al. (2015) document evidence of learning in response to SARS in Taiwan, although this is not mediated via ICTs.

[2]News of this embezzlement was first broken to the public in 2017 by a probe by Haiti's senate (Charles, 2017)

timestep and build a panel centered around this spell of social unrest. Then, we assign users into treatment if events of social unrest occur in close proximity to their three most used towers.

Using a two-way fixed effects specification (TWFE), we estimate negative treatment effects or positive effects of smaller magnitude. These results suggest contacts falls by 0.05 per day, duration of time spent talking increases by 15 seconds, and total calls fall by 0.175. This pattern of results suggests people might talk more to their close contacts and with fewer of their distant contacts. Furthermore, this story is consistent with evidence from disparate shocks such as earthquakes and stock crashes (Blumenstock et al., 2016; Romero et al., 2016). Using the DiD approach, we find largely contrary results, though we argue these suffer from a mix of selection biases. In particular, we estimate large, positive effects of treatment on social network activity. Social unrest increases the number of network contacts by about one half per day, the amount of time spent talking by 2.7 minutes per day, and the number of calls by about 1 per day. We argue that these results are due to targeting of social unrest to high call areas and the ability of those in these areas to anticipate and avoid spells of social unrest.

Evidence from heterogeneity in social unrest events supports this argument. Using the DiD approach we find significant heterogeneity which may be associated with the ability of users to anticipate an event. In particular, when examining number of contacts as an outcome, easy to anticipate events tend to have more positive effects, while hard to anticipate events have null or negative effects. These easy to anticipate events are also those which require greater coordination and are likely better targeted for the purposes of creating disruption. More concretely, protests, which are the easiest to anticipate of the five event types, have the largest positive effects. In contrast, rock throwing, which requires little coordination or resources, has almost equally large negative effects. While it is not clear, it may be the case that truly shocking events have a true effect of muting the number of contacts, whereas avoidance behavior may change response when coordination is high. However, when estimated using TWFE, we observe homogeneous negative treatment effects across all event types except for protest. Intuitively, this is because individual fixed effects control for the targeting and anticipation of other event types.

2 Background

2.1 Related Literature

2.1.1 Crises, Protests, and Diffusion of Information

Social networks are important in mobilizing political participation Campbell (2013). Several types of diffusion are important to distinguish here: word-of-mouth, mass media, social media, and movement organizations, i.e., the formal or informal core of activists. Word-of-mouth network diffusion outside of voluntary associations has not always played a central role. For example, in the diffusion of sit-in events in the southern United States in the 1960's, broad word-of-mouth diffusion took a back seat to mass media and movement organizations (Andrews and Biggs, 2006). This is intuitive when risk of personal harm is involved in the decisions to protest as it was during the sit-in movement. While information might often flow easily through word-of-mouth, when there is a risk associated with passing information on this may be restricted to within organizations where members have common goals. This contrasts with what appear to be more spontaneous forms of social unrest which arose during the Arab Spring. Steinert-Threlkeld et al. (2015) documents social media activity in 16 countries during the Arab Spring, finding that decentralized social media activity correlates with coordination of protests shortly thereafter.[3]

2.1.2 Social Network Response to Shocks

While considerable work has been devoted to social networks in the developing world, networks have often been viewed as fixed objects which serve to convey information or payments. From the literature we understand that social network structure matters for the diffusion and exchange of information (Banerjee et al., 2013; Beaman et al., 2015), informal risk management (Fafchamps and Lund, 2003; de Weerdt and Dercon, 2006; Ambrus et al., 2014), favor exchange (Jackson et al., 2012), and public goods provision (Bramoullé and Kranton, 2007; Cruz et al., 2020). In particular,

[3]Other work documents important aspects of diffusion in this context as well: Starbird and Palen (2012) documents retweeting activity of a popular meme during 2011 Egyptian political uprisings.

work on informal risk management deals specifically with the response of these networks to economic and environmental shocks. While much of this study has been devoted to network formation, the usage of these risk sharing networks in the wake of economic shocks has been clearly documented (Fafchamps and Lund, 2003; de Weerdt and Dercon, 2006; Ambrus et al., 2014). Less well studied is the impact of various crises on other forms of social network usage. Romero et al. (2016) is a notable and interesting exception which looks at the effects of price shocks on the communication network between employees at a hedge fund. During large stock price drops, the data shows increased siloing among closely connected members of the firm.[4]

Recently, an adjacent and vibrant literature has emerged emphasizing the response of social networks and social capital to development interventions and the expansion of markets. Gagnon and Goyal (2017) present a theoretical framework to understand how market participation and network participation might complement and substitute for each other. A number of studies consider changes in networks as an unintended consequence of the introduction of savings products, including Dizon et al. (2019), Dupas et al. (2019), and Comola and Prina (2020). Likewise, studies of the unintended consequences of microfinance products have been explored in Banerjee et al. (2021) and insurance products in Cecchi et al. (2016) and Takahashi et al. (2019). These have not always found consistent results. For example, Dizon et al. (2019) finds reductions in risk sharing network participation, while Dupas et al. (2019) finds that households become less reliant on family and more supportive of neighbors. Other work has looked at the expansion of community based development programs (Heß et al., 2018) and the effect of industrialization on social capital (Miguel et al., 2006).

2.1.3 Social, Economic, and Digital Networks

As access to administrative data has grown, digital trace data has become an attractive approach to understanding social and economic network structure. This data is highly detailed and maps intuitively into the data structures used in social network analysis. Calls, SMS, and mobile money

[4] Affectionately described as "turtling up."

products tend perform similar functions to their in-person counterparts. An interdisciplinary literature on measuring “online” social networks and comparing these to offline social networks. For example, Dunbar et al. (2015) find that Twitter and Facebook networks have similar contact frequency distributions as in person contacts. That is, for a given intensity of interaction, on average users interact with about the same number of people they might in an offline setting (e.g., as measured by survey).[5] Likewise, we see evidence of risk sharing remittances taking place over mobile money networks, handling locally correlated risks like weather and natural disasters (Jack and Suri, 2014; Blumenstock et al., 2016; Riley, 2018). Digital communication networks play a similar role to their in-person cousins. Explaining network structure in mobile networks as a function of value, Blumenstock et al. (2019) finds a preference for ‘interconnected’ mobile networks among migrants, which echoes results from in person social networks constructed around support and favor exchange (Jackson et al., 2012).[6]

2.2 Data and Context

2.2.1 Social Unrest in Haiti

To measures spells of social unrest, we use a timeline of social unrest events throughout 2019, taking into account kinds of unrest on various days throughout the year. Starting in 2018, Haiti has faced a period of social unrest in response to reports of government corruption and embezzlement of loans from Venezuela’s PetroCaribe program (Charles, 2017). This period included protests, roadblocks, shootings, rock throwing, and tire burning, among other events. The high-level view of this timeline can be seen in Figure 1. These spells of unrest were very disruptive. For example, they forced the cancellation of Carnival events in 2019 and 2020. On February 17th, prime minister Jean Henry Céant noted that “it’s been ten days since children have been unable to go to school, hospitals can’t provide healthcare, big businesses and small businesses can’t

[5] Other studies include Xu et al. (2014), who study the structure of online social networking sites, and Liu et al. (2012) who consider event-based social networks, as well as the previously mentioned Steinert-Threlkeld et al. (2015).

[6] Björkegren (2019) takes as that value derives from communication as a starting point, and models the adoption of mobile phones, using supply shocks to tower provision change the value of owning and communicating via mobile phone.

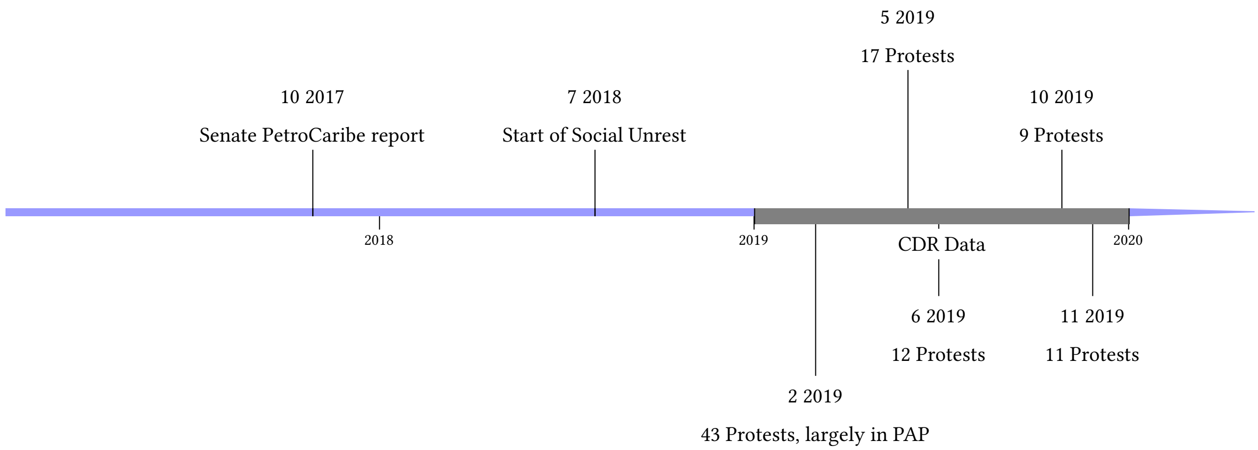

Figure 1: Highlights of Protest Events in Haiti, 2017-2019

function." Similarly, citizens noted dismay: "people can not eat," "the economy is bad, really bad" (Charles, 2019).

Using this timeline, we zoom in on those events taking place in January and February. The timeline itself draws on embassy security reports, newspaper articles, and social media activity to determine when and where social unrest took place (Pierre-Charles et al., 2020). The data contains information about the type of social unrest, geographic location, start time, and level of severity (as determined by the US embassy).[7] The types of social unrest identified are protests, roadblocks, shootings, rock throwing, tire burning, which covers the large majority of events throughout the year.[8] We plot these five forms of social unrest by their frequency in January and February in Figure 2. Notably, the increase in number of events in early February changed the codes used by the embassy provided security updates. While the earlier unrest was coded "avoid area," from the 7th to the 10th of February the code was upgraded to "home restriction." Finally, event on

[7]In particular, we apply the most likely coordinates to each event as possible. When an street intersection in mentioned in a report this is quite precise. When one of the many small neighborhoods are mentioned we defer to the coordinates of the main intersection in this neighborhood. These neighborhoods are relatively small and so even very imprecise placement in relatively large neighborhoods should be off by no more than 500m.

[8]The remaining unspecified events are dropped.

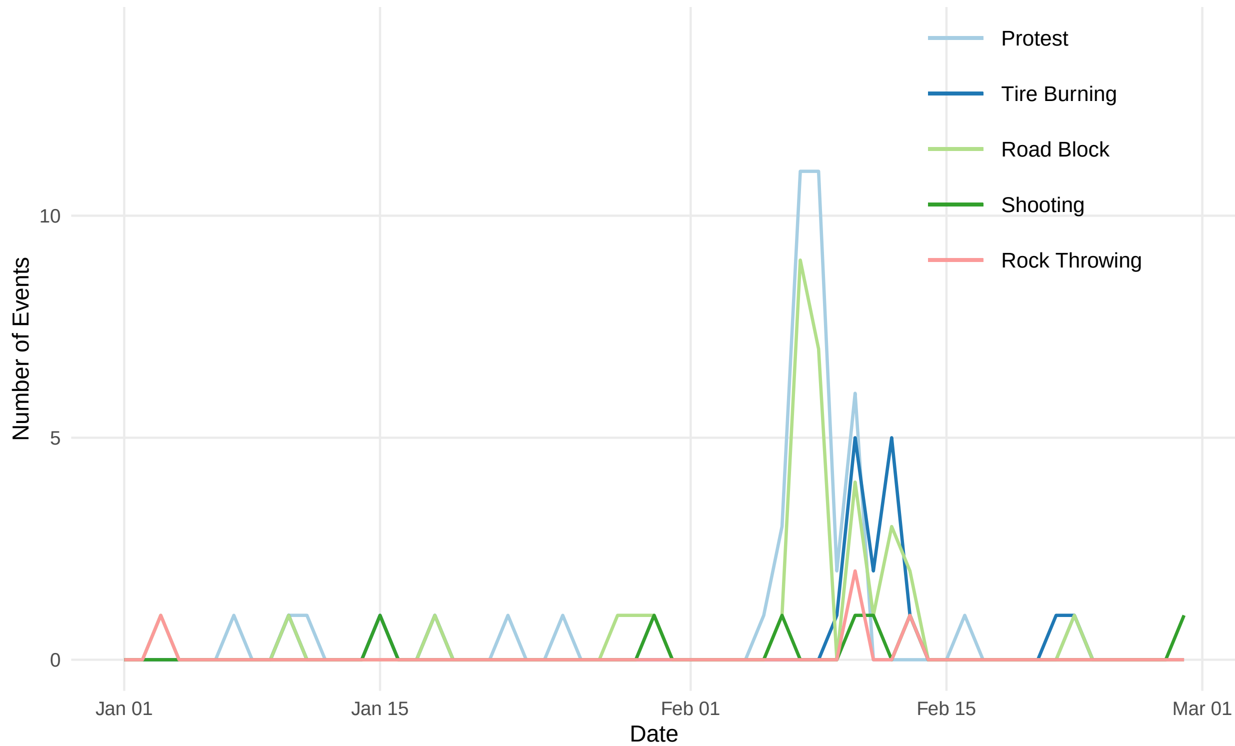

Figure 2: Number of Social Unrest Events by Day in Port-Au-Prince, January and February 2019

the 11th to the 21st carried a ”shelter in place” code before returning to ”avoid area” codes to end the month. To get a general sense of the location of unrest, we map of events in Port-Au-Prince in Figure 3 as well as the individual types of social unrest in Figures 6-10. Notably, when examining the disaggregated maps, one pattern emerges in the distribution of protests relative to other forms of social unrest. In particular, while protest clustered around Champs de Mars (along with the presidential palace and government administrative complexes), other events tended to cluster more to the east, in more residential areas.

These five forms of social unrest differ on a number of margins. One is the scale of coordination necessary for their occurrence. Leading the way are protests which require a high degree of coordination, enough to ensure a good turnout of protesters. Second is tire burning, which are reported to require around five experienced participants.[9] This is followed by roadblocks, which

[9]“How many people does it take to burn a tire?” is a question with an answer: typically five. Two people carry the tire, two carry gasoline or some other inflammatory substances, and the last one lights the tire with a match (or lighter). See Anonymous (2015) for more.

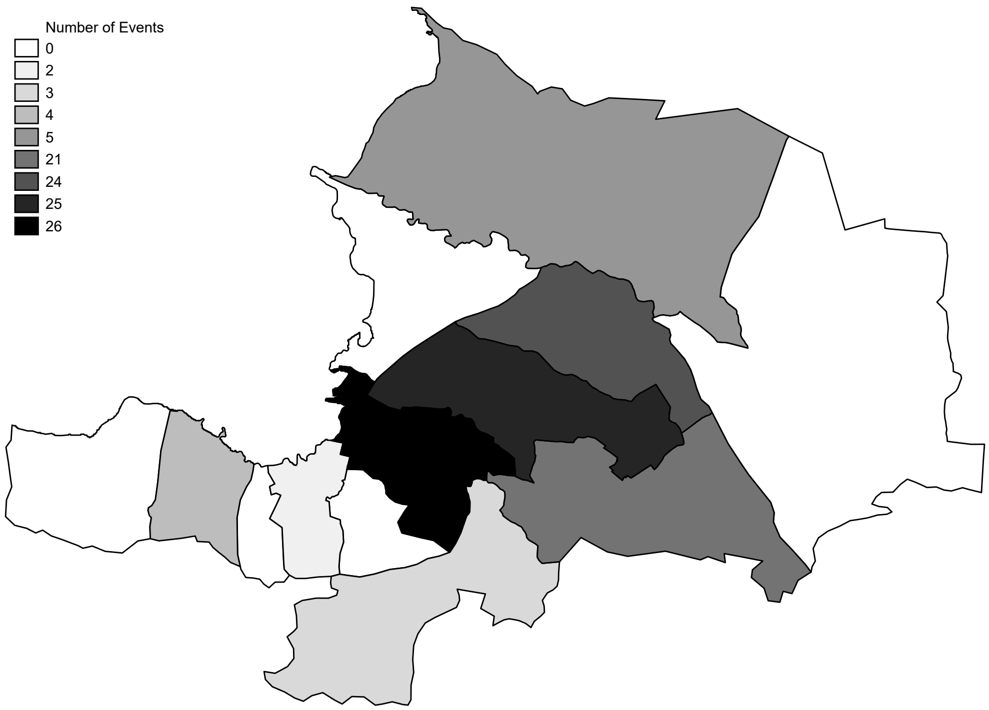

Figure 3: Social Unrest Events in Port-au-Prince, January and February 2019.

require just enough people to move a car or some other impediment.[10] Finally, shootings and rock throwing feature require the lowest level of coordination.

Other margins we can consider include the possibility of anticipation and how geographically local they are. Notably, while protests may be most disruptive, they are also possible to anticipate due to their high degree of coordination.[11] The other events are less easy to anticipate, and some (shooting and rock throwing) are considerably more spontaneous than others. Likewise, it's important to consider the geographic scale. It's intuitive that both protests and roadblocks have implications that extend beyond their specific location as they often take place on main thoroughfares and thus have the ability to jam up the city. In contrast, shooting, tire burning, and rock throwing may be the most acute in localities.

[10]This could be more than five people, but needs not be, so the minimum to create such a roadblock could happen with lower coordination. Of course, it could also feature more coordination in specific cases.

[11]The participants must have heard about the protests in advance, so others probably did too.

2.2.2 Mobile Phone Metadata

The mobile phone metadata used in this project comes from Digicel, the largest telecommunications provider in Haiti. Digicel has a dominant market share in the Haitian telecommunications market, reducing worries about sampled networks (Chandrasekhar and Lewis, 2016). The data includes transaction-level records of calls and text messages: caller id, recipient id, datetime, duration in second (0 for SMS), caller tower, recipient tower (not included for SMS or calls out of network), and traffic type (voice or SMS), often referred to as Call Detail Records (CDRs). The data covers all of 2019 and will serve as our measure of network connection (Digicel Haiti, 2019).

2.2.3 Call Outcomes

To construct outcomes to test these hypotheses, we focus on individual cellphone usage. These outcomes included the number of unique contacts, total calls, and total duration, each of which has an analogue in social network centralities. First, we compute degree centrality, yielding the the number of unique contacts in a day for all nodes. Second, we can compute "weighted" degree centralities which yield both the total number of calls each day and the total duration of those calls.

3 Theoretical Model

We construct a model of network response that builds on the model presented in Björkegren (2019). In particular, we model the response of those who are exposed to social unrest by geographic proximity. Our adaption differs in a number of ways from the original model. First, while the model is used in that work to understand calling behavior as a motivation for handset adoption, we find it useful to model the calling decision as an end unto itself. Second, the model there provides structure for the empirical exercise. Here, we use the model as a vehicle to generate hypotheses, but do not extend it to provide structure for our estimates. Still, we find some features of the model very useful. In particular, the utility gained from making calls accords with eight reasonable properties related to demand for calling, at least six of which remain relevant in this context. Therefore, we adapt the utility function, embedding within it a model of expectations about the informational value of calling specific network neigbhors during crisis.

3.1 Utility and Cost Functions

We specify the following function for the value of calls:

$$v_{ij}(d_{ijt}, \epsilon_{ijt}) = \alpha_{ij} d_{ijt} - \frac{1}{\epsilon_{ijt}} \frac{d_{ijt}^{\gamma}}{\gamma}. \tag{1}$$

where d is duration (in seconds), ϵ is a communication shock, $\gamma > 1$ controls the decline of marginal returns, α controls the intercept for marginal utility of calling. Note that we allow α to depend on both the caller i and the receiver j, which embodies tie strength, which plays an important role in the results of the model. In relative terms, those with high values of α can be thought of as strong ties and those with low value, weak ties. Likewise, the communication shock $epsilon$ plays an important role in the model. In particular, this shock reflects the informational content to i of a call to j conditional on the social unrest on day t.[12]

We suppose no fixed costs but a marginal cost of calling c_{it}.

$$c_{it} = p + \phi(z_{it}) \tag{2}$$

where p is per second price of calling and ϕ is an "attention" cost of calling, which depends on social unrest, z_{it}. The intuition here is that as social unrest strikes (whether engaging in labor or leisure) people become more vigilant monitoring their surroundings. Phone calls are a distraction from monitoring one's environment and therefore this reduction in attention adds to the cost of making a call which is linear in call duration. The utility and cost functions are an adaption

[12]These shocks are complex objects. While we abstract away from this, in reality, we can think about this as a mix of expectations and the actual value of information gained after a call begins. For example, I might expect my friend has a great deal of information about the current unrest, but they may relate to me that they do not after I call them, adjusting down the "shock" and ending my call.

of those used in Björkegren (2019) which features eight reasonable properties for cellular call behavior, six of which are also important in this application:[13]

1. Zero call duration yields zero utility, $v(0, \epsilon) = 0$
2. Diminishing marginal returns to call duration, $v(d, \epsilon)$, is concave in d
3. For some values of the parameters a call is placed; The optimal duration yields non-negative utility, $v(d^*, \epsilon) \geq 0$ where d^* solves $\frac{\partial v(d^*,\epsilon)}{\partial d} = c$ or is zero.
4. Even if calls are free, a caller won't talk forever. That is, even when marginal cost equals zero, there is a duration d^* where $\frac{\partial v(d^*,\epsilon)}{\partial d} = 0$
5. Changing the cost of a call changes the extensive decision to call. This requires the marginal utility of calling to be finite at zero. $\frac{\partial v(0,\epsilon)}{\partial d} < \infty$.
6. Changing the marginal cost of a call affects longer calls more than shorter calls, $\frac{\partial^2 d^*}{\partial c \partial \epsilon} < 0$

These six properties can be verified for the adapted utility function.

3.2 Caller's Problem

The callers problem is as follows:

$$\max_{d_{ijt} \geq 0,\ j \in N(i)} U_i(\mathbf{d}_t) = \sum_{j \in N(i)} \left[\frac{1}{\beta} v_{ij}(d_{ijt}, \epsilon_{ijt}(z_{it})) - (p + \phi(z_{it}))d_{ijt} \right] \tag{4}$$

[13] In particular, Björkegren (2019) uses the utility function

$$v(d, \varepsilon) = d - \frac{1}{\epsilon} \left[\frac{d^\gamma}{\gamma} + \alpha \right] \tag{3}$$

and features two more properties. First, that the amount of information learned in a call maps to duration. There is an one-to-one mapping of duration to information with an analytic solution, $\epsilon(d^*)$. Second, that relationships with higher information flows provide more utility. The optimized utility is increasing in the optimal duration, $\frac{\partial v(d,\epsilon(d))}{\partial d} > 0$. These are both important and useful as the paper estimates a structural model to do welfare analysis. The first recovers the error or shock term from the model and the second allows for welfare analysis. However, in the context of our analysis, neither exercise is planned.

where $N(i)$ is agent i's neighborhood and β coverts from utils to dollars. In addition, we allow the information shock to depend on social unrest, z_{it}, since social unrest drives the search for information.

3.3 Call Duration

Setting marginal cost equal to marginal utility, when $d_{ijt} > 0$ we arrive at a solution of

$$d^*_{ijt}(\epsilon_{ijt}(z_{it}), \phi(z_{it})) = \left[\epsilon_{ijt}(z_{it})\left(\alpha_{ij} - \beta\left(\phi\left(z_{it}\right) + p\right)\right)\right]^{\frac{1}{\gamma-1}}. \tag{5}$$

When is $d_{ijt} = 0$? In this model, in cases where any positive duration yield negative utility, no call is made. Since $v_{ij}(d = 0) = 0$, the caller chooses a duration of zero over any positive duration. In particular, when

$$\alpha_{ij} < \beta(\phi(z_{it}) + p) \tag{6}$$

a call will not be made.[14]

3.4 Comparative Statics

3.4.1 Very Weak Ties Are Not Called During Social Unrest

To construct hypotheses about the response of social networks to social unrest, we examine how calls and call duration change when social unrest is "switched on." Let $\Delta\phi(z_{it}) = \phi(z_{it} = 1) - \phi(z_{it} = 0)$. Furthermore, let $\phi(z_{it} = 0) = 0$ as in the absence of social unrest we assume there is no relevant threat to pay attention to. Given $\Delta\phi(z_{it}) > 0$ condition 6 yields a first prediction about the decision to call: attention cost driven by social unrest reduces the set of alters one will talk when they are proximate to social unrest. We refer to those who no longer place calls after social unrest, or those j where $\alpha_{ij} > \beta p$ but $\alpha_{ij} \leq \beta(\phi(z_{it}) + p)$ as very weak ties. If there is any

[14] While we take the neighborhood of i as given, this expression can also be thought of as a way to implicitly define neighborhood. If $\alpha_{ij} \leq \beta p$, then no calls will ever be made between i and j regardless of social unrest. Therefore, $j \notin N(i)$.

Table 1: Heterogeneous Responses of Dyadic Calling Behavior to Social Unrest

Ranges of α_{ij}			$d^*_{ijt}(z_{it}=1)$	$\Delta d^*_{ijt}(z_{it})$
	α_{ij}	$\leq \beta p$	$=0$	$=0$
$\beta p <$	α_{ij}	$\leq \beta(\phi_{it}+p)$	$=0$	<0
$\beta(\phi_{it}+p) <$	α_{ij}	$< \beta\left(\frac{\phi_{it}+(\phi_{it}+p)\%\Delta\epsilon_{ijt}}{\%\Delta\epsilon_{ijt}}\right)$	>0	<0
	α_{ij}	$= \beta\left(\frac{\phi_{it}+(\phi_{it}+p)\%\Delta\epsilon_{ijt}}{\%\Delta\epsilon_{ijt}}\right)$	>0	$=0$
$\beta\left(\frac{\phi_{it}+(\phi_{it}+p)\%\Delta\epsilon_{ijt}}{\%\Delta\epsilon_{ijt}}\right) <$	α_{ij}		>0	>0

Note: $\%\Delta\epsilon_{ijt} = \frac{\Delta\epsilon_{ijt}(z_{it})}{\epsilon_{ijt}(z_{it}=1)}$ and $\phi_{it} = \phi(z_{it})$.

number of these very weak ties in the average network neighborhood, we should expect some reduction in the set of contacts one calls on the day of social unrest.

3.4.2 Other Responses Depend on Tie Strength and Information Shocks

Second, we consider the impact of social unrest on relationships that would have positive call duration during social unrest, which we will refer to as strong ties.

$$\begin{aligned}\Delta d^*_{ijt}(\epsilon_{ijt}(z_{it}), \phi(z_{it})) = &\left(\frac{1}{\gamma-1}\right)\left[\epsilon_{ijt}(z_{it})\left(\alpha_{ij} - \beta\left(\phi\left(z_{it}\right)+p\right)\right)\right]^{\frac{1}{\gamma-1}-1} \\ &\times \left[\Delta\epsilon_{ijt}(z_{it})\left(\alpha_{ij} - \beta\left(\phi(z_{it})+p\right)\right) - \beta\epsilon_{ijt}(z_{it})\Delta\phi\left(z_{it}\right)\right]. \qquad (7)\end{aligned}$$

We simplify this expression:

$$\Delta d^*_{ijt}(\epsilon_{ijt}(z_{it}), \phi(z_{it})) = d^*_{ijt}(z_{it}) \times \frac{\Delta\epsilon_{ijt}(z_{it})\left(\alpha_{ij} - \beta\left(\phi(z_{it})+p\right)\right) - \beta\epsilon_{ijt}(z_{it})\phi(z_{it})}{(\gamma-1)[\epsilon_{ijt}(\alpha_{ij} - \beta(\phi(z_{it})+p))]} \qquad (8)$$

$d^*_{ijt}(z_{it}) > 0$ implies $(\alpha_{ij} - \beta(\phi(z_{it})+p)) > 0$, and $\gamma > 1$. Therefore, the sign of the derivative depends only on the sign of the expression

$$\Delta\epsilon_{ijt}(z_{it})\left(\alpha_{ij} - \beta\left(\phi(z_{it})+p\right)\right) - \beta\epsilon_{ijt}(z_{it})\phi(z_{it}). \qquad (9)$$

Call duration increases for those dyads where this expression is positive. Several different manipulations of this expression are useful. First, to build intuition, we express the inequality such that response is positive as a ratio compared to one:

$$\left(\frac{\Delta\epsilon_{ijt}(z_{it})}{\Delta\phi(z_{it})}\right)\left(\frac{\alpha_{ij}-\beta\left(\phi(z_{it})+p\right)}{\beta\ \epsilon_{ijt}(z_{it})}\right)>1. \tag{10}$$

The sign of the effect depends on the ratio of the effect of social unrest on informational content of calls (how much more do we have to learn from person j when the world becomes more uncertain?) to the effect of social unrest on attention cost (how much more of your environment do you miss when chatting on the phone when the world becomes uncertain?). Additionally, the likelihood this condition holds increase in dyads with pre-existing strong ties (α_{ij}), falls in costs to i ($\beta\left(\phi(z_{it})+p\right)$), and attenuates the more informational content calling along that dyad had in the first place ($\epsilon_{ijt}(z_{it})$).

Second, we characterize the bound where the value switches from negative to positive in terms of the strength of α_{ij}. This gives us an expression similar to 6. For a given dyadic shock to attention cost and information, if

$$\alpha_{ij}>\beta\left(\frac{\phi(z_{it}=1)+(\phi(z_{it}=1)+p)\frac{\Delta\epsilon_{ijt}(z_{it})}{\epsilon_{ijt}(z_{it})}}{\frac{\Delta\epsilon_{ijt}(z_{it})}{\epsilon_{ijt}(z_{it})}}\right) \tag{11}$$

then we will see an increase in call duration.

Duration response is summarized in table 1. Note that as the percentage change in information shock grows, the right hand expression in inequality 11 converges to $p+\phi(z_{it})$, as is plotted in figure 4. This suggests that when the information shock is sufficiently large, even relatively less strong ties will almost always be contacted more given that call duration is positive. Likewise, when the percentage increase in information is sufficiently small, ties will need to be increasingly large to allow for an increase in call duration.

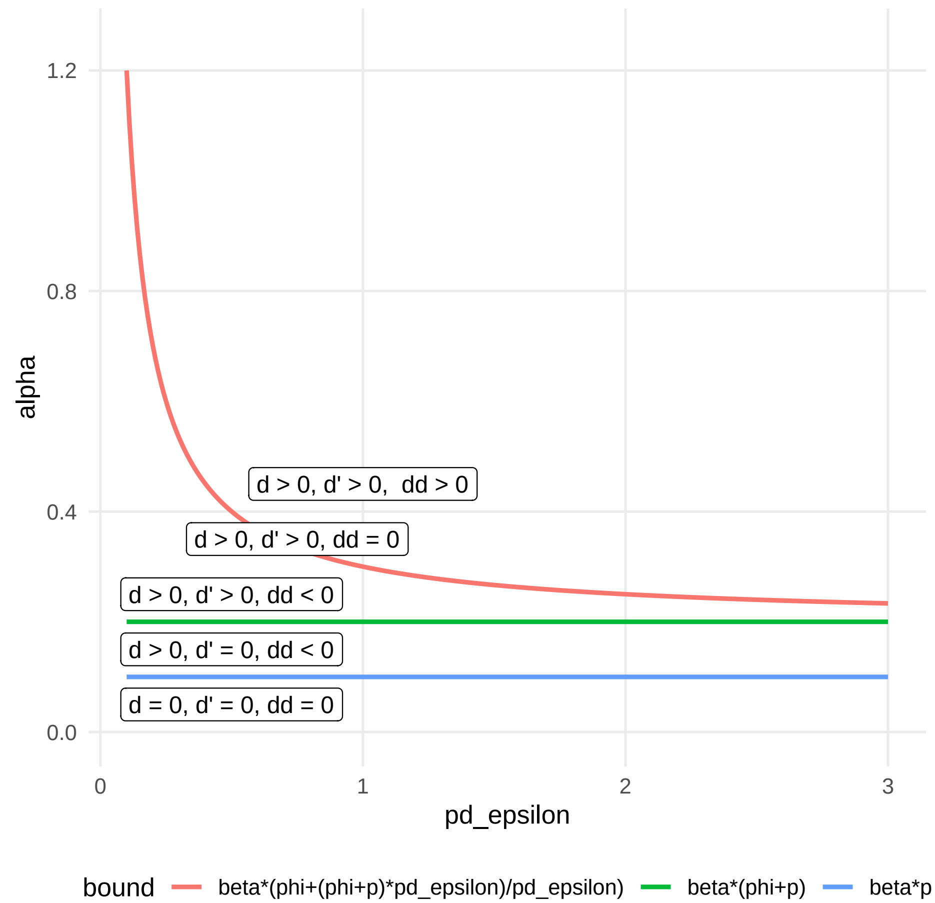

Figure 4: Call response by tie strength and information shock. d is duration with no social unrest, d' is duration with social unrest and dd is the difference in duration. pd_epsilon is the $\%\Delta\epsilon_{ijt}$ and alpha is α_{ij}. Assumes values of $\phi_{it} = p = 0.1$ and $\beta = 1$.

3.4.3 Aggregation of Dyadic Effects to Neighborhood

Translating to neighborhood level calling behavior, the impact on total is the sum of the impacts on dyadic call duration:

$$\frac{\partial}{\partial z_{it}} \left\{ \sum_{j \in N(i)} d^*_{ijt}(\epsilon_{ijt}, p) \right\} = \sum_{j \in N(i)} d^*_{ijt} \times \frac{\epsilon'_{ijt}(z_{it})\left(\alpha_{ij} - \beta\left(\phi(z_{it}) + p\right)\right) - \beta\epsilon_{ijt}(z_{it})(\phi'(z_{it}))}{(\gamma - 1)[\epsilon_{ijt}(z_{it})(\alpha_{ij} - \beta(\phi(z_{it}) + p))]} \tag{12}$$

However, because these impacts depend on j, we cannot make a prediction about the effect on neighborhood level calling behavior without some idea about the dyad level parameters α_{ij} and shocks ϵ_{ijt}.

Considering the number of contacts who are called, the more weak ties there are the neighborhood, the more the number of contacts will fall. In particular, this reduction in contacts would be the case in a situation where for some households, condition 6 switches on during social unrest. We presume there are some weak tie individuals in an average network neighborhood, so we would expect a reduction on average in the number of contacts made during social unrest.

However, even when there is a reduction in the number of contacts called, there could easily be an increase in total duration, if for sufficient other nodes we find that condition 9 holds.[15] Given that this depends the composition of parameters in the neighborhood, we need to proxy for these parameters to build predictions about total duration response. While α should be closely related to past duration of calls, ϵ has much less structure. Therefore, to make informed predictions about we need to explore heterogeneity that might augment the information shock along a given dyad.

3.5 Network Structure and Information Shocks

While we have taken network structure into account when considering strong and weak ties, based on the model we have derived, we have left information shocks as exogenous and without structure. To better guide our hypotheses, it may be worthwhile to consider how information might flow in our context. Three considerations are made. First, we suppose that those who are more central from the perspective of receiving information diffusion will invite higher information shocks in the wake of social unrest. Second, those who's information is more differentiated from others' will also feature higher information shocks. Third, those who are also proximate to social unrest may know more and therefore have a greater information shock.

[15]One useful piece of intuition might come from the sixth feature of the utility function. In particular, changing the marginal cost of a call affects longer calls more than shorter calls. This would suggest that attention cost will yield more resistance against those who already call often, i.e., those with strong ties and or high shocks. This would suggest more of the impact might come from previously low duration callers where information has grown.

3.5.1 Diffusion Centrality

Similarly to Banerjee et al. (2019), we posit that even while individuals do not know the full structure of their surrounding network, they have strong priors about who in their neighborhood is informed, based on who they hear information and gossip from in previous cases. Thus we posit that ϵ_{ijt} depends specifically on expectations of neighbors ability to aggregate information. This brings to mind the "hearing matrix" presented in Banerjee et al. (2019), which considers the concept of diffusion centrality presented in Banerjee et al. (2013) from a receivers perspective.[16]

King (2020) presents three additional concepts that refine diffusion centrality: *word-of-mouth*, *obstructed*, and *visibility* centrality.[17] King (2020) makes the argument that diffusion centrality double counts information flows, and designs word-of-mouth centrality to create a similar measure while removing the double counting. Obstruction centrality and visibility centrality both look at a case where some node does not pass information within word-of-mouth centrality. In this case, these may benefit the measurement in our context. In particular, we would prefer a world where the ego node is excluded from the diffusion process at hand, since information passed from the ego to an alter and back to the ego will not be informative. Obstructed centrality measures the average probability a node will receive signals sent by others, when that signal is obstructed by any of the other nodes in the network.[18]

[16]In this, the hearing matrix is defined as

$$\mathbf{H}(\mathbf{D}, S) = \sum_{s=1}^{S} \mathbf{D}^s \tag{13}$$

and network gossip, or the expected number of times a node j will hear a given piece of news as a function of the node of origin of the information, is

$$NG(\mathbf{D}, S)_j = H(\mathbf{D}, S)_j. \tag{14}$$

[17]Bramoullé and Genicot (2018) also presents two concepts in *targeting centrality* and *reachability*. Adapting diffusion centrality to targeted requests for favors, the authors arrive at targeting centrality. Second, they provide a formula to compute reachability of an agent in a network, or the probability a request will reach them. Again, while these measures are related to what we want, they emphasize how easy it is to target or reach a given node from the perspective of the node trying to inform them of a request. Instead we want a measure that gives a general sense of how informed we expect a node is, given their social network.

[18]The cost of this refinement from concepts of word-of-mouth centrality is that the centrality of each alter j will be defined separately for each ego i. We can restrict this to $j \in N(i)$ to be more efficient, building a sparse matrix of centralities.

3.5.2 The Strength of Weak Ties

In addition to the ability to aggregate information, it is reasonable to consider the importance of weak ties in the diffusion of information. An early presentation of this concept is featured in Granovetter (1973), but has seen development since as bridging (as opposed to bonding) social capital (Woolcock and Narayan, 2000). In our model, this might be embodied by a negative correlation in the strength of tie and the novelty of information.[19] We can proxy for this type of tie using edge betweenness centrality, which measures how often ij is on the shortest network paths between other nodes within the network. This encapsulates the brokerage feature of bridging social capital.

3.5.3 Alter Proximity to Social Unrest

Finally, those who are also close to other social unrest events may be better informed, and may find themselves with larger information shocks due to this proximity. To the degree that agents have some idea of generally where social unrest is taking place, this should impact calling behavior.

3.6 Hypotheses

From this model, stylized facts about social networks, and the acuteness of the social unrest shock in this context, we arrive at five hypotheses:

H1: *Social unrest leads to higher network usage.* As social unrest takes place, information shocks become large on average as the surrounding environment becomes unpredictable. On average, there are enough ties that are strong enough conditional on these information shocks to increase total duration of calls.

H2: *Weak ties are not called regardless of information shocks.* People communicate with those

[19]One note is that as the existence of "structural holes" becomes important after significant but incomplete diffusion has taken place. If no diffusion has not already taken place over the relevant information, the difference in information between subgroups is limited by the scarcity of information.

they have sufficiently strong ties to but not those weakest (positive) ties. This leads to a reduction in the number of people called during social unrest

H3: *Medium-strength and strong ties are sought out according to their information shock.*

(a) Call duration increases along high information medium-strength ties, some low information strong ties, and high information strong ties. Search for information drives people to increase call duration along high information dyads even when they are only medium strength ties. Sometimes, call duration increase for strong ties even when the information shock is relatively small. Call duration increases the most among high duration strong ties, as they have both personal and informational value.

(b) Call duration falls for low information medium-strength ties, some low information strong ties, and even high information ties with sufficiently low strength of tie. However, call duration remain above zero for these medium and strong ties.

H4: *Diffusion occurs.* This prediction does not come from the model, but a natural extrapolation of the behavior described above. We hypothesize that neighbors of those who are in affected areas also have higher network usage, which we will interpret as evidence of information diffusion.

4 Empirical Strategy

4.1 Difference-in-Differences

I use a difference-in-differences strategy to estimate the response of social networks to social unrest. The empirical strategy of this paper is based on geographic variation in social unrest. This strategy does not rely on random assignment of social unrest, but rather on the assumption of parallel trends.

To tie the empirical approach to the archetypal difference-in-differences approach, we will first present the estimating equation for DiD. For simplicity, we consider event-time where $t = 0$

when social unrest first takes place:

$$y_{ilt} = \alpha + \beta \, \text{Unrest}_{il} + \gamma \, \text{Post}_t + \delta \, \text{Unrest}_{il} \times \text{Post}_t + \epsilon_{ilt} \tag{15}$$

where Unrest_{il} is an indicator variable equal to 1 if individual i in area l dealt with an episode of social unrest and Post_{lt} is an indicator variable equal to 1 during and after the the episode.

However, the archetypal DiD specification may be a poor fit for this context. DiD is meant to pick up a policy change, where the policy switches "on" in perpetuity (i.e., treatment is an absorbing state). However, here we see a brief uptick in social unrest, a change which switches "on" and then "off" again. Therefore, in the case where we are estimating the instantaneous treatment effect, we allow treatment to switch off. Therefore we can re-write the specification as

$$y_{ilt} = \alpha + \beta \, \text{Unrest}_{il} + \gamma \, \text{Episode}_{lt} + \delta \, \text{Unrest}_{il} \times \text{Episode}_{lt} + \epsilon_{ilt} \tag{16}$$

where Episode_{lt} is an indicator variable equal to 1 when unrest is taking place. Finally, we have considerable individuals who use each tower, and we are able to utilize individual fixed effects to estimate this specification with two-way fixed effects:

$$y_{ilt} = \alpha_i + \gamma \text{Episode}_{lt} + \delta \, \text{Unrest}_{il} \times \text{Episode}_{lt} + \epsilon_{ilt} \tag{17}$$

In addition to technical assumptions needed to establish causality, interpreting the treatment effect is similarly important. A key fact in this interpretation is that the protests were disruptive to society but do not directly impact the infrastructure of the cell phone network, so the degree of damage to towers was minimal. This closes off any supply side channel that might impact usage and isolates treatment to the demand side.

4.2 Network Measurement

A first potential threat to validity and laid out in Chandrasekhar and Lewis (2016) comes from network sampling. However, since we have administrative data from a telecom provider with a large market share, this should allow for "census-like" conditions. Therefore, we can treat networks as if they are not sampled. Relying on the results presented in Chandrasekhar and Lewis (2016), we are confident the sampling rate is sufficient to dismiss worries about sampled networks.

In interpreting my results as saying something about social networks, we rely on the fact that communications networks are a good proxy for the true social networks of interest that may exist over multiple "platforms." One issue that might arise in particular, is that the use of smart phones has grown in Haiti over the past few years. Therefore, we may not observe the full effect of social unrest on digital communication due to app based calling and messaging apps (e.g., WhatsApp). we might be able to observe a proxy for smartphone messaging over time by looking at cellphone data usage over time, but we are not able to observe communication that take place via WhatsApp and other messaging services.

Another potential issue is that of how mobile communication networks relate to social networks in total. These networks will of course capture some portion of users' social networks, given that social communication is taking place along these channels. However, one could imagine that there is some degree of substitution between in-person communication and mobile communication. Since we do not observe (surveyed) social networks we cannot rule out that this is the case. However, it is important to note that in the case of a positive treatment effect, any substitution effect would have to outweigh the effect of social unrest on networks for these results to differ qualitatively from the proxy at hand.

4.3 Data Processing, Estimation, and Standard Errors

After cleaning, we process transactions from voice calls made in Haiti in the month of February 2019 into a set of network graphs and a list of users.

4.3.1 Data Cleaning

To clean the data, we remove all transactions involving irregular length of prefix (i.e., length 3 as opposed to 5) international calls. Second, we drop all transactions that do not start with a standard 509 Haiti calling code. This has the sum effect of removing all international calls as well as those related to information, emergency and corporate numbers. Next we remove any number that is not associated with a cellphone tower, which are likely landlines, but cannot be observed as calling in the dataset.

4.3.2 Assignment of Nodes to Treatment

I focus on social unrest taking place in the greater Port-Au-Prince region. Particularly in February, social unrest was centered in Haiti's largest city and was geographically differentiated within the city. Additionally, areas outside of Port-Au-Prince do not make good comparisons to the city. Finally, our data quality both in terms of cell service coverage likely do not do jusitice to the areas outside of Using this logic, we filter cellphone towers to be within the greater PAP region.[20] Next, we match these towers to protest events that happened within one kilometer of the tower. We view this as a relatively inclusive band, but a reasonable one. In particular, it roughly captures the differences between thoroughfares in Port-Au-Prince. Since events of social unrest tend to occur on these thoroughfares, this should capture only one thoroughfare at a time with its surrounding neighborhood. Additionally, since not every event is perfectly precise, we feel that this distance does a good job including those in the actual radius of the event. Using this data, we create a list of treatments by tower and by date, which we merge to the user-tower file. we aggregate the user-tower dataset over the course of the month, recording all towers used by a given user. Then, we match this user-tower file to the tower list featuring treatment status. Because those with higher usage might also have higher mobility (this tends to be true), we only assign treatment

[20] To do this, we select sub-commune boundaries, better known as communal sections (ADM4) to capture the urban core of Port-au-Prince and its direct surroundings. These sections include Petit Bois, Varreux (Croix-des Bouquets), Bizoton, Rivière-Froide, Thor, Bellevue, Saint Martin, Varreux (Delmas), Bellevue Chardonnieres, Etang du Jong, Martissant, Morne L'Hopital, and Turgeau.

status to an individual if an unrest event happened at one of the three towers where they made the greatest number of calls over that month (which we call a top-3 tower).

4.3.3 Constructing Nodes, Edgelists and Network Statistics

Starting with the clean transaction data, for each day in February, we construct two summary files. First, we construct user-tower files, aggregating the number of calls a user made from a given tower or received at the same tower over the course of that day. Users will serve as nodes in the network, but tower is preserved to assign them to "treatment" later. In this file, we record the number of calls made and received each day. Second, we construct edgelists, records of all calls between two numbers over the course of that day. In these edgelists, we compute three undirected measures of the network: if the two users called each other, how many times they called one another, and the total duration of these calls. Finally, we compute network statistics for each node using these three measures. In particular, for each node and each day we compute network degree by summing up usage by that node; first unweighted, and then weighted by number of calls and finally by call duration. Taking a list of all users who make calls within the Port-Au-Prince area, we merge treatment and network statistics to these users day by day and compile these into a panel. Because networks are constructed at a country-wide level this does not drop calls or texts to those outside of PAP.

4.3.4 Estimation and Standard Errors

All specifications are estimated in R using felm from the lfe package. While standard errors are not clustered, this is a priority for future work, clustering by either the neighborhood of the most used tower or e.g., two-way by the top two neighborhoods.

Table 2: Effects of Social Unrest on Network Degree

	(Unweighted) Degree	
	(1)	(2)
treat	0.493***	−0.054***
	(0.002)	(0.001)
ever_treated	1.826***	
	(0.001)	
Day FE	Yes	Yes
Indv. FE	No	Yes
N	61,757,976	61,757,976
R^2	0.035	0.640
Adjusted R^2	0.035	0.627
Residual Std Err	3.872	2.409
RSE df	61757946	59552306
Notes:	***Significant at the 1 percent level.	
	**Significant at the 5 percent level.	
	*Significant at the 10 percent level.	

5 Results

5.1 Main Effects

The TWFE estimator, my preferred specification, suggests that while the number of contacts and calls per day falls, duration spent conversing increases. Interestingly, this bears resemblance to results from Romero et al. (2016) and Blumenstock et al. (2016). This pattern of results might imply people talking more to their close contacts. This story is intuitive and is my working hypothesis, though more evidence is needed to confirm it's validity. Using the DiD approach, we estimate large, positive effects of treatment on social network activity. In particular, we estimate that social unrest increases network degree/usage regardless of the outcome measure used. When using TWFE estimates differ considerably. This is consistent with two stories. The first story is that social unrest is targeted towards higher activity areas, biasing the DiD specification. Second, that events that are easy to anticipate allow for avoidance behavior by those high activity users,

Table 3: Effects of Social Unrest on Total Call Duration

	Duration Weighted Degree	
	(1)	(2)
treat	162.021***	14.782***
	(0.920)	(0.670)
ever_treated	493.817***	
	(0.637)	
Day FE	Yes	Yes
Indv. FE	No	Yes
N	61,757,976	61,757,976
R^2	0.012	0.521
Adjusted R^2	0.012	0.504
Residual Std. Error	1,802.793	1,277.963
RSE df	59552306	48524094

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

similarly biasing the DiD specification. The pattern of results for all these specifications can be represented using t-statistics, which are plotted in Figure 11.

The unweighted ego-treatment regressions (see Table 2) yield two contradictory sets of results depending on the specification of choice. For the event-only DiD regression, we observe a large increase in the number of people contacted by those near an unrest event on the day the event occurs. This increase is 0.493, or about half an additional contact in that day.[21] From this specification, we also see that those who are treated by social unrest at any point during the month have about 1.8 more contacts per day. The TWFE regression yields a contrary result. In particular, we observe a reduction in the number of contacts on the day of treatment. This reduction is 0.054 contacts on the day of treatment, only about one-tenth the magnitude of the effect in the DiD specification.

[21] Due to sample size, coefficients tend to enter significantly into the regressions at a 1% level. Thus, we discuss their magnitude as opposed to statistical significance. In the case that coefficients enter at a lower significance level this will be noted, as well as precise zeros.

Table 4: Effects of Social Unrest on Total Calls

	Call Weighted Degree	
	(1)	(2)
treat	0.999***	−0.175***
	(0.005)	(0.003)
ever_treated	3.954***	
	(0.003)	
Day FE	Yes	Yes
Indv. FE	No	Yes
N	61,757,976	61,757,976
R^2	0.031	0.613
Adjusted R^2	0.031	0.599
Residual Std. Error	9.122	5.870
RSE df	61757946	59552306
Notes:	***Significant at the 1 percent level.	
	**Significant at the 5 percent level.	
	*Significant at the 10 percent level.	

Moving on to duration weighted degree specifications (see Table 3), where the outcome is the total time spent conversing on the phone with alters in seconds, we have a more consistent story. In particular, we see positive treatment effects in both the DiD and TWFE estimates. First, in the DiD event only specification estimates that total duration of calls increases by 162 seconds, or 2.7 minutes on the day of the social unrest. The estimates from the TWFE model are much smaller. In particular, these suggest the total duration of calls increases only about 15 seconds.

Finally, looking at call-weighted degree specifications (in Table 3), we observe a similar pattern to the unweighted degree outcomes. In particular, we observe an increase in the number of calls for those who were treated when using the DiD specification, and a reduction while using the TWFE specification. The magnitude is also somewhat consistent, the size of the treatment effect in the DiD specification is about 5 times the size of the treatment effect in the TWFE specification (in absolute value).

Table 5: Heterogeneous Effects of Social Unrest on Degree

	Degree	
	(1)	(2)
protest	0.195***	−0.021***
	(0.002)	(0.002)
ever_protest	1.085***	
	(0.001)	
tire_burning	0.035***	−0.135***
	(0.004)	(0.002)
ever_tire_burning	0.205***	
	(0.001)	
road_block	0.056***	−0.073***
	(0.003)	(0.002)
ever_road_block	0.448***	
	(0.001)	
shooting	−0.005	−0.090***
	(0.004)	(0.003)
ever_shooting	0.698***	
	(0.001)	
rock_throwing	−0.169***	−0.104***
	(0.006)	(0.004)
ever_rock_throwing	0.263***	
	(0.001)	
Day FE	Yes	Yes
Indv. FE	No	Yes
N	61,757,976	61,757,976
R^2	0.050	0.640
Adjusted R^2	0.050	0.627
Residual Std. Error	3.842 (df = 61757938)	2.409 (df = 59552302)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

5.2 Are Treatments Heterogeneous?

I explore heterogeneity in social unrest, disaggregating treatment effects by event type. Considering the disaggregated results of regressing degree (daily contacts) on social unrest, we observe impacts broadly similar to those in the main specification. However, the heterogeneity in treatments does not confirm the earlier aggregation of protest events by intensity. Instead, we find significant heterogeneity which may be associated with the degree of coordination required to stage such an event, which also makes these events easier to anticipate.[22] In this specification, hard to anticipate events have more negative effects on communication. In particular, shooting and rock throwing are low coordination and are thus more difficult to anticipate. While shooting is a precise zero, rock throwing puts a large damper on communications, a 0.169 contact reduction per day. Medium coordination events are tire burning and road blocks. Interestingly, these events all effect towers with users who have more contacts than average relative to place where they do not happen, regardless of their treatment effect. I.e., This suggests that all forms of social unrest seem to target areas where high volume users locate.

Considering the construction of treatment above, where one is treated if a protest, road block, or shooting takes place within a kilometer of your top-3 cell phone tower, we find evidence that this treatment may not be homogeneous, particularly in the DiD specification. Overall, hard to anticipate events have null or negative effects in this specification, while easy to anticipate events have positive effects. More concretely, protests, which are the easiest to anticipate of the five event types, have the largest positive effects. In contrast, rock throwing, which requires little coordination or resources, has almost equally large negative effects. While it is not clear, it may be the case that truly shocking events have a true effect of muting contacts, whereas avoidance behavior may change response when coordination is high. Looking at the homogeneous treatment effects in particular, shooting enters as a precise zero (1/200th fewer contacts), in contrast to road blocks and protests. The results from the TWFE specifications contrast with those from the

[22]If events are coordinated using social media as in the Arab Spring, it would be hard to have one without the other.

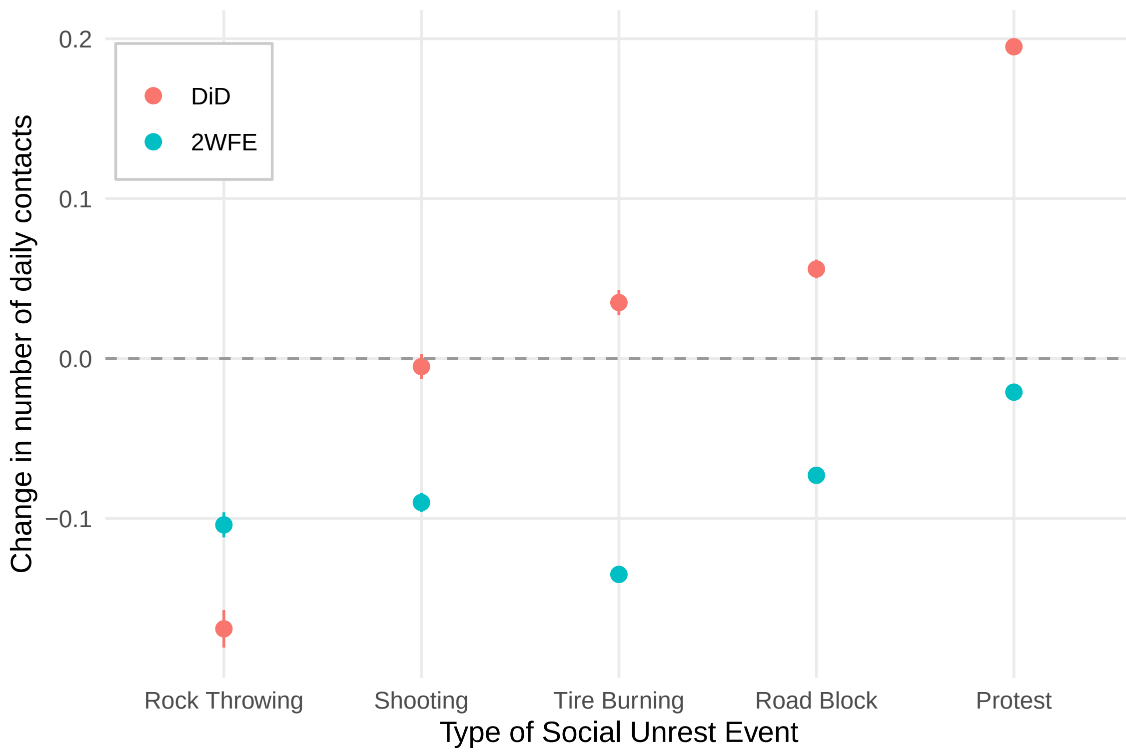

Figure 5: Pattern of effects on unweighted degree by type of social unrest.

DiD specification in a way that mirrors the main effects. When controlling for individual effects, we observe homogeneous negative treatment effects across all event types except for protest. Intuitively, this is because individual fixed effects can control for the targeting and anticipation of other event types. This pattern of results is plotted in Figure 5. Overall, evidence from heterogeneity in social unrest events is consistent with stories presented above about how protest is targeted and how avoidance behavior might take place.

6 Conclusion

6.1 Summary

In this paper, we estimate the treatment effect of social unrest on social networks using call networks in Haiti as a proxy for social networks. While significant work is needed to refine the estimation and interpretation of these effects, some interesting preliminary results appear.

Notably, we observe very different effects depending on specification. These include large positive effects on network activity in the case of the DiD estimator and reduction in calls and contacts but a small increase in duration in the case of the TWFE estimator. While these contrasting estimates may indicate an unclear relationship between social unrest and network response, we argue that the TWFE estimate is more credible in this case due to the targeting of social unrest and the ability of individuals to avoid social unrest. This paint a story where people reach out their close friend (or their close friends reach out to them) when their neighborhood is the sight of social unrest.

6.2 Towards Network Change

The evolution of networks has long been of interest to economists and other computational social scientists remains an important goal of our broader project.[23] Pulling apart usage in networks from changes in the underlying networks is difficult, and beyond the scope of the current work. Most important in taking steps from understanding network usage to network change is understanding and specifying a relationship between the flow of usage and the "social capital" of the network state. Additionally, alternative econometric approaches to those used in this work will be demanded, including the specification of treatment as an absorbing state and estimation of econometric models of network formation. The former will open up a world where dynamic treatment effects are possible using event study methodologies while the latter will allow us to investigate how specific dyads embedded within the network change over time.

[23]See, for example, Jackson and Watts (2002).

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Additional Figures

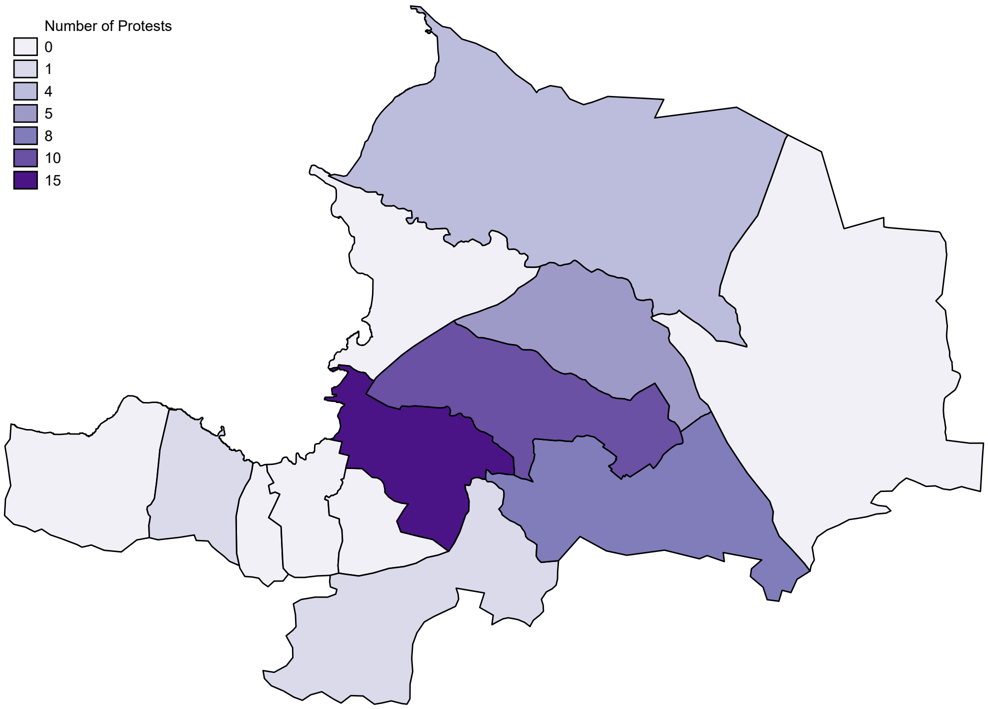

Figure 6: Protests in Port-au-Prince, January and February 2019.

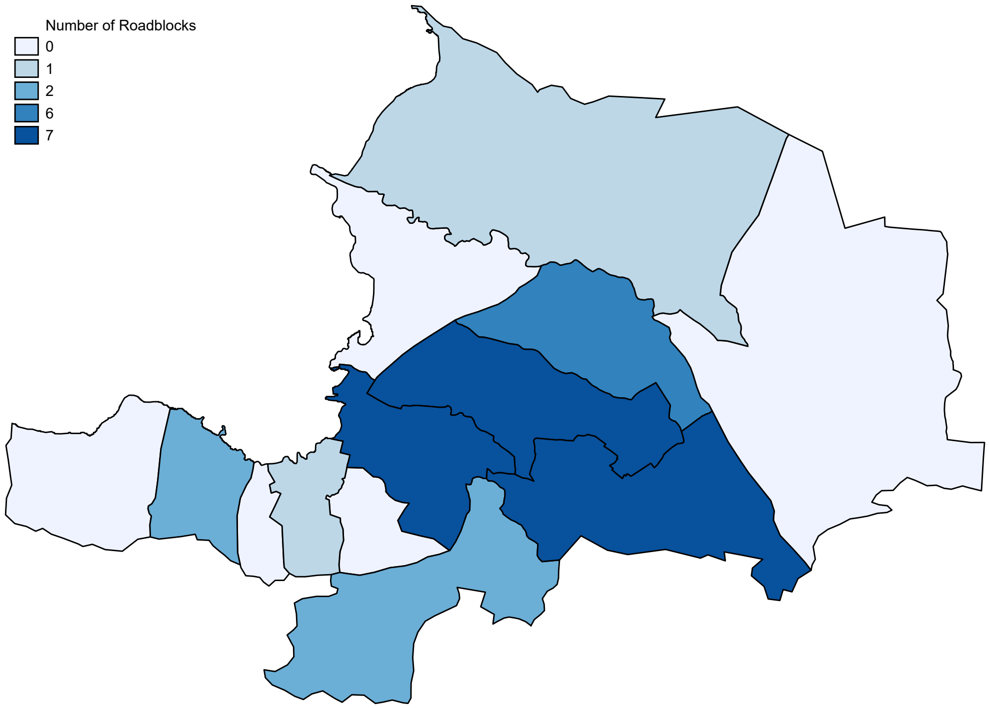

Figure 7: Roadblocks in Port-au-Prince, January and February 2019.

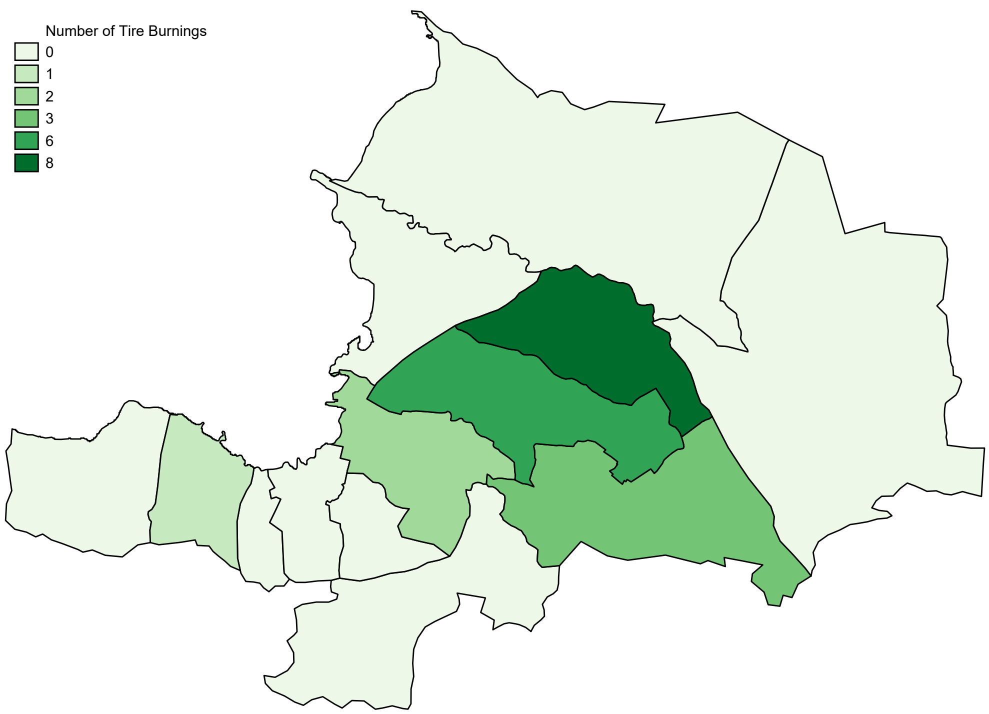

Figure 8: Tire Burning Events in Port-au-Prince, January and February 2019.

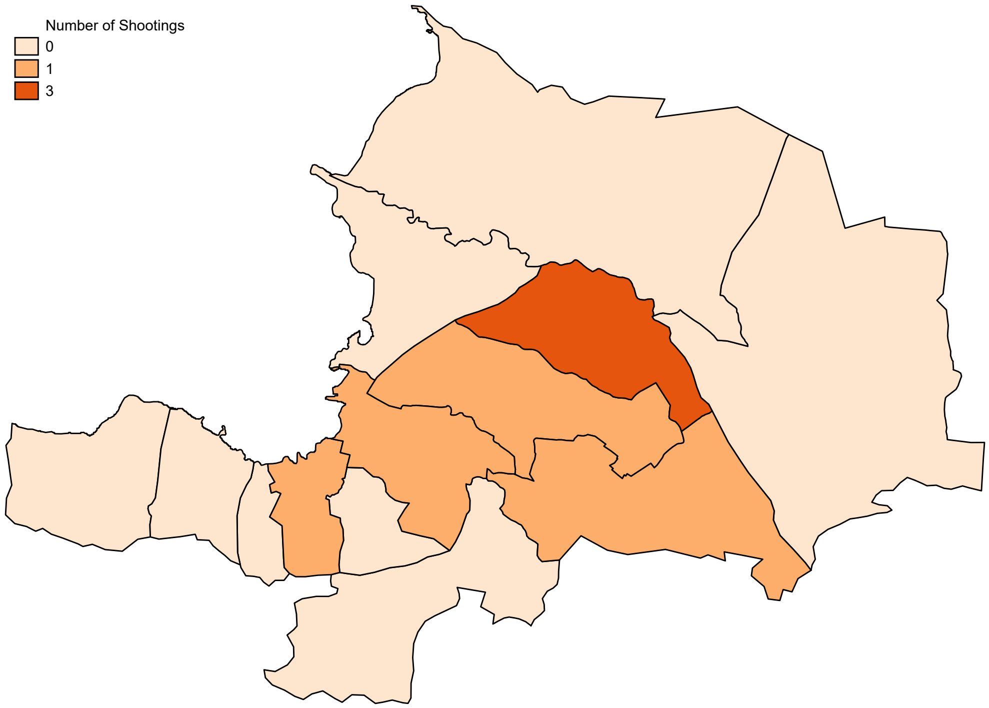

Figure 9: Shootings in Port-au-Prince, January and February 2019.

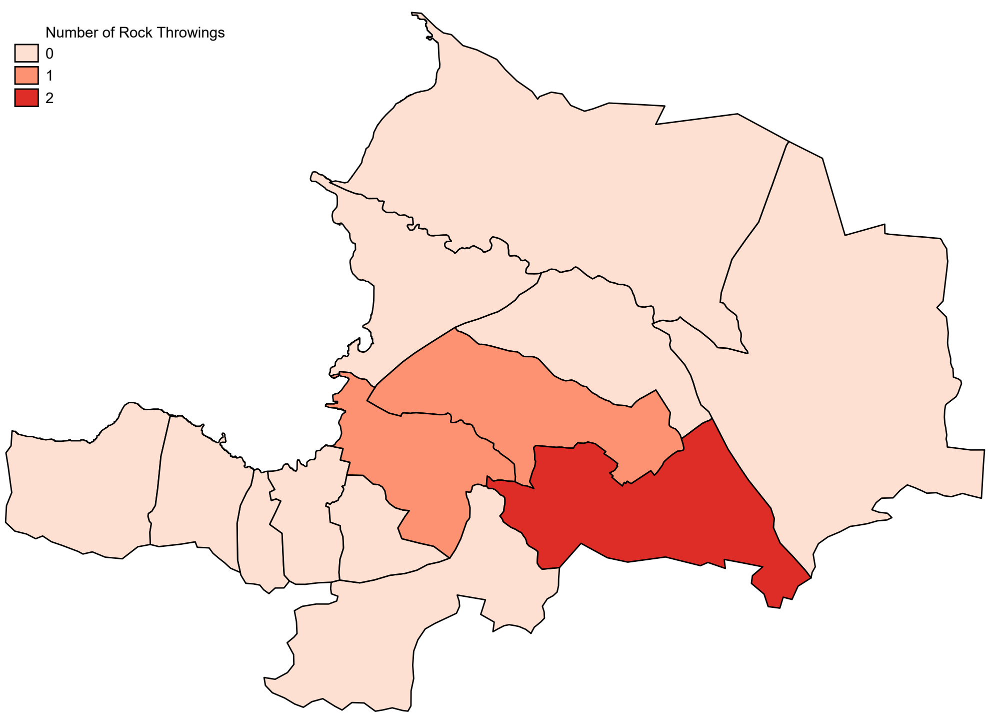

Figure 10: Rock Throwing Events in Port-au-Prince, January and February 2019.

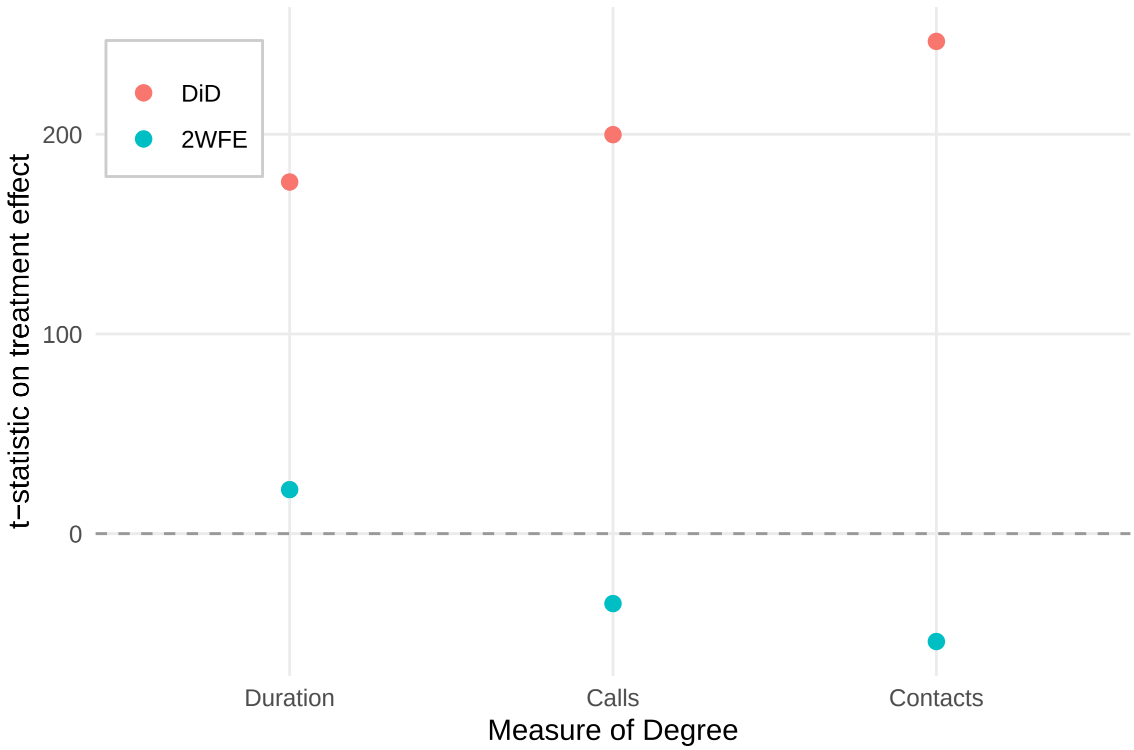

Figure 11: Pattern of t-statistics across specifications for degree measures.