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 less predictable of these events to estimate how calling behavior responds from day-to-day. Estimating treatment effects with both TWFE and a difference-in-differences estimator robust to heterogeneous treatment effects and staggered treatment adoption, we find that contacts and calls decrease, but talk time duration remains constant. These results are consistent with predictions from a theoretical model of social network response to social unrest.

Keywords: Social Networks, Social Unrest, Digital Trace Data, Call Detail Records, Mobile Phone, Haiti

JEL Codes: L14, O12, Z13

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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 by considering how these localized shocks shift incentives to communicate throughout these networks. 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 and the implications of this response for these networks.

A few prior studies similarly study how social networks as reflected in ICT usage 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 unexpectedly 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. We similarly 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 rely instead on a smaller network consisting of strong and trusted ties?

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.

Our empirical strategy is three-fold. First, we argue that these spatially isolated shocks serve as a natural experiment suitable for a modified difference-in-differences empirical strategy. Second, we restrict to the least predictable events – excluding protest from our definition of treat-

[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)

ment. Third, we pay careful attention to the weighting of tower specific treatment effects as these are aggregated into the average treatment effect. In particular, we utilize the DID^M estimator presented in de Chaisemartin and D'Haultfœuille (2020) as well as TWFE to estimate instantaneous treatment effects of as areas of Port-au-Prince fall into and out of spells of social unrest. Using this empirical strategy, we estimate the network response using mobile phone metadata from a large telecommunications provider in Haiti as a proxy for social 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 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 most used towers.

We construct a model of network response to social unrest which builds on work by Björkegren (2019). In this model, the effect on calling behavior depends on the underlying strength of social connection, how informed ones peers are about this unrest relative to the price of calling and an attention cost one pays to monitor one's surroundings during these moments of unrest. The model predicts that the most weak ties will not be contacted, but that other ties will be contacted when they have higher information shocks or are stronger ties. Using these prediction, we hypothesize that social unrest will lead to higher duration due to the increases in information shock, reduction in contacts who are very weak ties, and medium strength ties called according to their information shocks.

Our main results use non-protest social unrest as our treatment of interest. Over five weeks from January 21st to February 24th, using the DID^M estimator we find that contacts falls by 0.048 per day, total calls fall by 0.103 per day, but duration of time spent talking stays roughly constant. This pattern of results suggests people might talk more with their strongly connected contacts and with fewer of their less connected contacts, consistent with the hypotheses of the from the theoretical model described above (though not with our extrapolation of those hypotheses). Furthermore, this story is consistent with evidence from disparate shocks such as earthquakes and stock crashes (Romero et al., 2016; Blumenstock et al., 2016; Jia et al., 2021).

We diagnose differences between TWFE and DID^M where these differences should be attributable to differences in weighting by the estimators in the presence of heterogeneous treatment effects or staggered treatment adoption. We find that the weighting provided by TWFE yields substantial differences in treatment effects, consistent with tests introduced by de Chaisemartin and D'Haultfœuille (2020). These results represent an early application of a frontier method, and the difference between results in this context demonstrate the improvement in our estimates over naive approaches.

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, 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

[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.

[4]Affectionately described as "turtling up."

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 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]

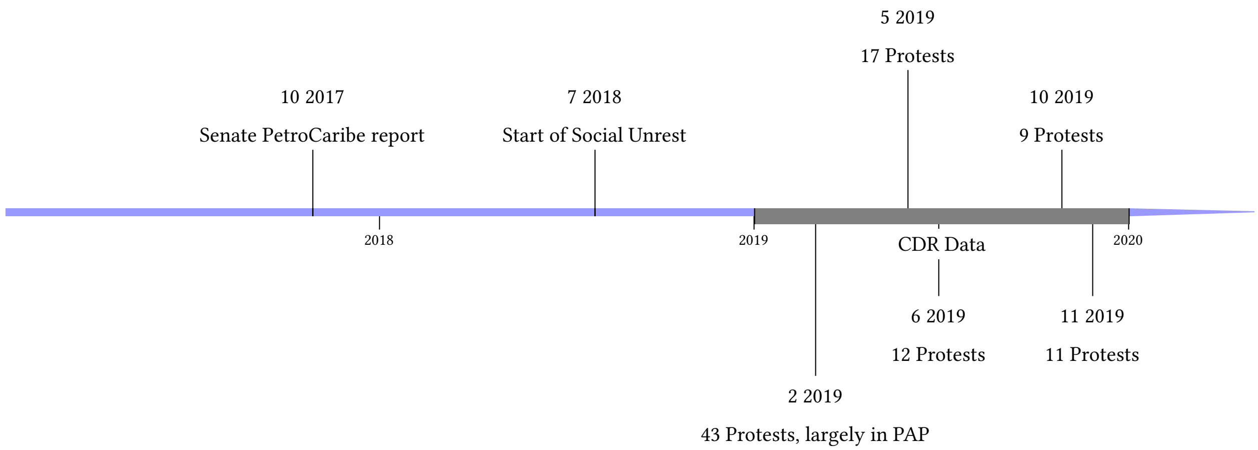

Figure 1: Highlights of Protest Events in Haiti, 2017-2019

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

[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.

(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 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 9-13. 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

[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.

[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.

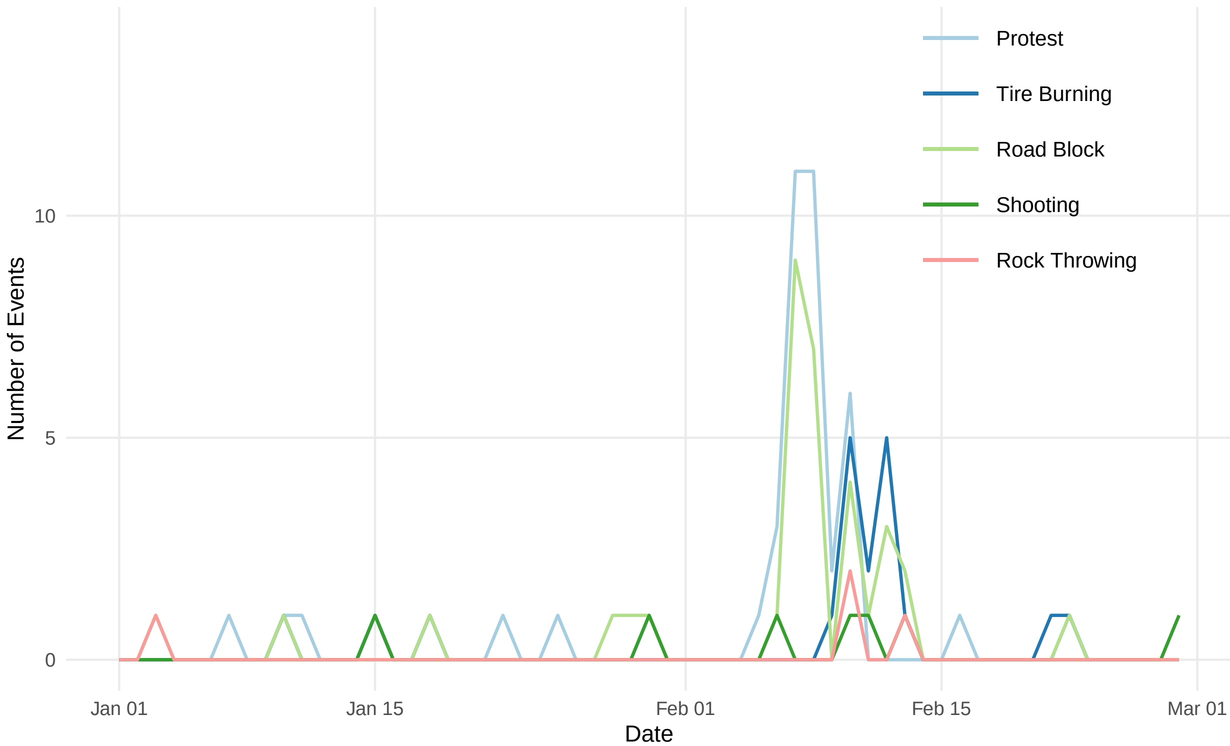

Figure 2: Number of Social Unrest Events by Day in Port-Au-Prince, January and February 2019

require just enough people to move a car or some other impediment.[10] Finally, shootings and rock throwing 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.

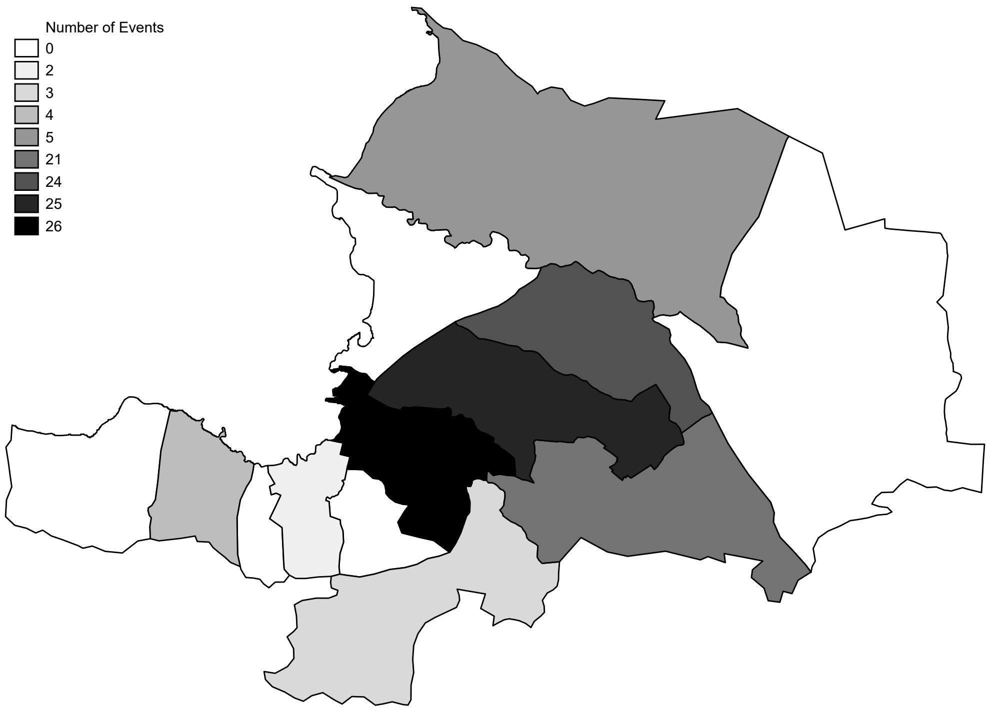

Figure 3: Social Unrest Events in Port-au-Prince, January and February 2019.

2.2.2 Mobile Phone Metadata

The mobile phone metadata used in this project comes from the largest mobile networks operator in Haiti as part of a long-term research collaboration that gives us access to these data. This mobile network operator has a dominant market share in the Haitian telecommunications market, which reduces concerns about sampled networks (Chandrasekhar and Lewis, 2016). Metadata like this is often referred to as Call Detail Records (CDRs) and, in our case, includes transaction-level records of calls and text messages: caller id, recipient id, date time, duration of calls in seconds, caller tower, recipient tower (not included for SMS or calls out of network), and traffic type (voice or SMS), . Under the auspices of our research agreement, we have access to multiple years of CDRs from this network operator, but in this analysis we use data from 2019 and use communication patterns as reflected in these data as the basis for constructing latent social networks.

Table 1: Baseline Outcomes

Statistic	Mean	SD	Median
Degree	18.2	26.3	11
Calls	88.5	135.0	38
Duration (seconds)	10815.8	20463.9	3038

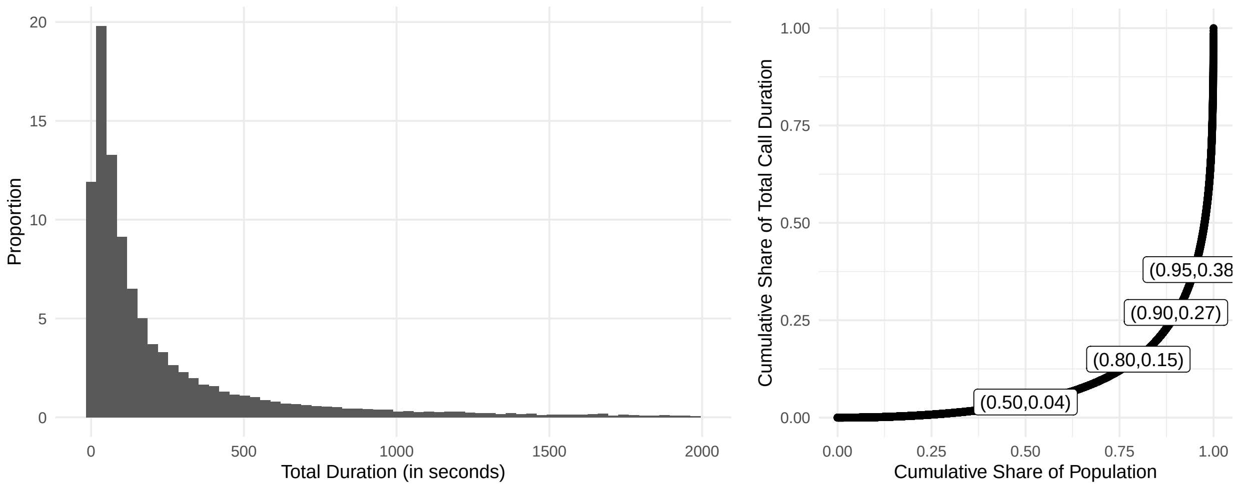

Figure 4: Histogram (left) and Lorenz curve (right) of total call duration over dyads in baseline network

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. We compute a baseline network of voice calls using data from the first three weeks of the year. Table 1 presents these statistics at baseline.[12]

[12]We also compute the global clustering coefficient of the graph to measure how tightly knit the graph is as a whole. More specifically, clustering coefficient answers the question: if i is connected to j, who is also connected to k, what is the probability that i also connected to k? In the baseline network, we find a clustering coefficient of 2.7% suggesting many "friends of friends" are unknown to the ego.

2.2.4 Defining Strong Ties in the Data

To differentiate between the strength of network connections prior to the onset of the 2019 unrest episodes, we leverage communication patterns as represented in the CDRs during this baseline period. Specifically, we use total duration of calls between individuals in the baseline network to define strong ties. Since the histogram of the total duration of calls (figure 4) does not betray any "natural" breaks in the distribution that would serve as logical points of differentiation, we opt for a simple statistical approach to imposing these cutoffs. We use the mean total call duration between individuals to differentiate strong ties from other edges in the network. Given that this duration distribution is skewed, the mean call duration is around the 81st percentile. We designate dyads with total call duration higher than this percentile to be strong ties. The Lorenz curve of total duration in the right panel of Figure 4 provides a visual depiction of this variation and associated implications for our strong tie distinction: Dyads in the lowest 80% of total call duration amount to only 16% of the total call duration whereas the bottom 90% account for 27% of the dyadic call duration, or an additional 11%. We can therefore think of the edges in this decile as a reasonable grouping of "average" connections to be included or excluded from strong ties. We opt to leave them in as a measure of average ties or stronger, and choose 80% as our main strong tie cutoff. At a later stage, we will check the sensitivity of our estimates to this cutoff assumption.[13]

[13]We considered two other alternatives, which are based on finding natural non-linearities at which to make cutoffs. A first approach is to compute the Jaccard index for each edge in the baseline network and use this to guide to making a cut-off in total duration, which measures the proportion of friends two people hold in common:

$$\text{Jaccard}(i,j) = \frac{\text{Total number of overlapping connections between } i \text{ and } j}{\text{Total number neighbors of } i \text{ of } j} \tag{1}$$

Closely related, the second approach is to simplify this to check whether edges are "supported" or not, that is if there exist any common connection, or if Jaccard$(i,j) > 0$. Both of these approaches appeal to the concept of *bonding social capital* , which is often measured by the triadic structure of networks (Woolcock and Narayan, 2000). Support in particular has been shown to be important in the formation of favor networks (Jackson et al., 2012) and the communications networks of migrants (Blumenstock et al., 2019). Computation of the Jaccard index turns out to be computationally very slow in our baseline network, but we hope to do so in the future in order to validate the approach that we opted for.

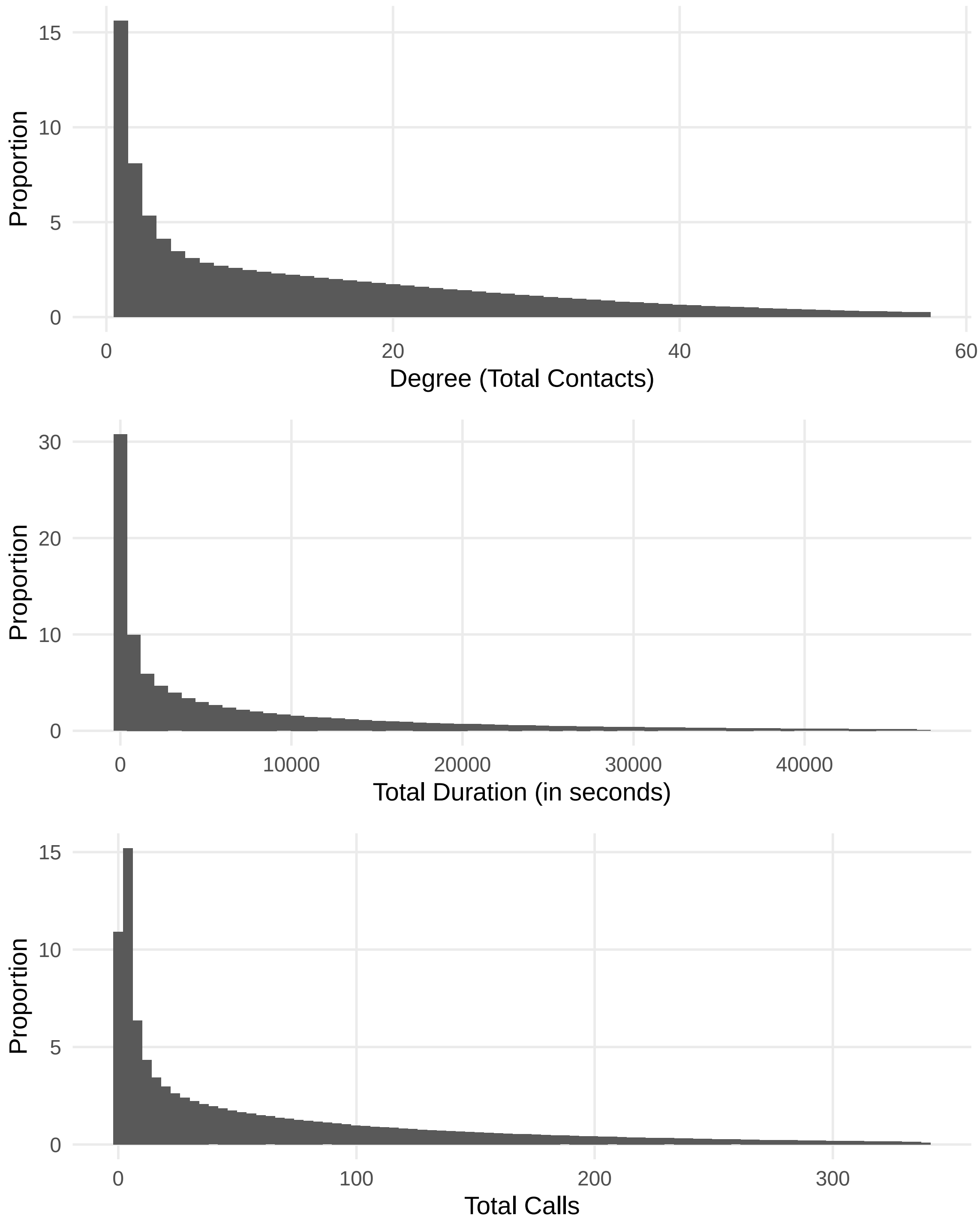

Figure 5: Histogram of node level outcomes in baseline network

2.2.5 Locating Likely Informed Nodes

We hypothesize that nodes with high degree at baseline are likely to be well informed when social unrest takes place. Therefore, to proxy for likely informed nodes, we plot the degree (as well as other network statistics) of these nodes in the baseline in figure 5. The distribution is right skewed for degree, with a median of 11, but a mean of 18. We choose a value above the mean as the cutoff for informed nodes, in this case 30. This corresponds to roughly the 67th percentile of this statistic in the baseline.

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 neighbors during crisis.

3.1 Utility and Cost Functions

We specify the following function for the value of calls:

$$v_{ij}(d_{ijt}, \epsilon_{ijt}) = \alpha_{ij} d_{ijt} - \frac{1}{\epsilon_{ijt}} \frac{d_{ijt}^{\gamma}}{\gamma}. \tag{2}$$

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.[14]

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

$$c_{it} = p + \phi(z_{it}) \tag{3}$$

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 of those used in Björkegren (2019) which features eight reasonable properties for cellular call behavior, six of which are also important in this application:[15]

1. Zero call duration yields zero utility, $v(0, \epsilon) = 0$

[14]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.

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

$$v(d, \varepsilon) = d - \frac{1}{\epsilon}\left[\frac{d^\gamma}{\gamma} + \alpha\right] \tag{4}$$

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.

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:

$$\max_{d_{ijt} \geq 0,\ j \in N(i)} U_i(\mathbf{d}_t) = \sum_{j \in N(i)} \left[\frac{1}{\beta} v_{ij}(d_{ijt}, \epsilon_{ijt}(z_{it})) - (p + \phi(z_{it})) d_{ijt} \right] \tag{5}$$

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

$$d^*_{ijt}(\epsilon_{ijt}(z_{it}), \phi(z_{it})) = \left[\epsilon_{ijt}(z_{it}) \left(\alpha_{ij} - \beta \left(\phi\left(z_{it}\right) + p\right)\right)\right]^{\frac{1}{\gamma - 1}}. \tag{6}$$

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

Table 2: 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 $\phi_{it} = \phi(z_{it})$.

duration. In particular, when

$$\alpha_{ij} < \beta(\phi(z_{it}) + p) \tag{7}$$

a call will not be made.[16]

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 7 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 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.

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

We simplify this expression:

$$\Delta d^*_{ijt}(\epsilon_{ijt}(z_{it}), \phi(z_{it})) = d^*_{ijt}(z_{it}) \times \frac{\Delta\epsilon_{ijt}(z_{it}) \left(\alpha_{ij} - \beta \left(\phi(z_{it}) + p\right)\right) - \beta\epsilon_{ijt}(z_{it})\phi(z_{it})}{(\gamma - 1)[\epsilon_{ijt}(\alpha_{ij} - \beta(\phi(z_{it}) + p))]} \tag{9}$$

$d^*_{ijt}(z_{it}) > 0$ 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

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

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:

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

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

[16]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, $j \notin N(i)$.

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 7. For a given dyadic shock to attention cost and information, if

$$\alpha_{ij} > \beta\left(\frac{\phi(z_{it}=1)+(\phi(z_{it}=1)+p)\frac{\Delta\epsilon_{ijt}(z_{it})}{\epsilon_{ijt}(z_{it})}}{\frac{\Delta\epsilon_{ijt}(z_{it})}{\epsilon_{ijt}(z_{it})}}\right) \tag{12}$$

then we will see an increase in call duration.

Duration response is summarized in table 2. Note that as the percentage change in information shock grows, the right hand expression in inequality 12 converges to $p+\phi(z_{it})$, as is plotted in figure 6. 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.

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:

$$\begin{aligned}\frac{\partial}{\partial z_{it}}\left\{\sum_{j\in N(i)} d^*_{ijt}(\epsilon_{ijt},p)\right\} = \\ \sum_{j\in N(i)} d^*_{ijt}\times\frac{\epsilon'_{ijt}(z_{it})\left(\alpha_{ij}-\beta\left(\phi(z_{it})+p\right)\right)-\beta\epsilon_{ijt}(z_{it})(\phi'(z_{it}))}{(\gamma-1)[\epsilon_{ijt}(z_{it})(\alpha_{ij}-\beta(\phi(z_{it})+p))]}\end{aligned} \tag{13}$$

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

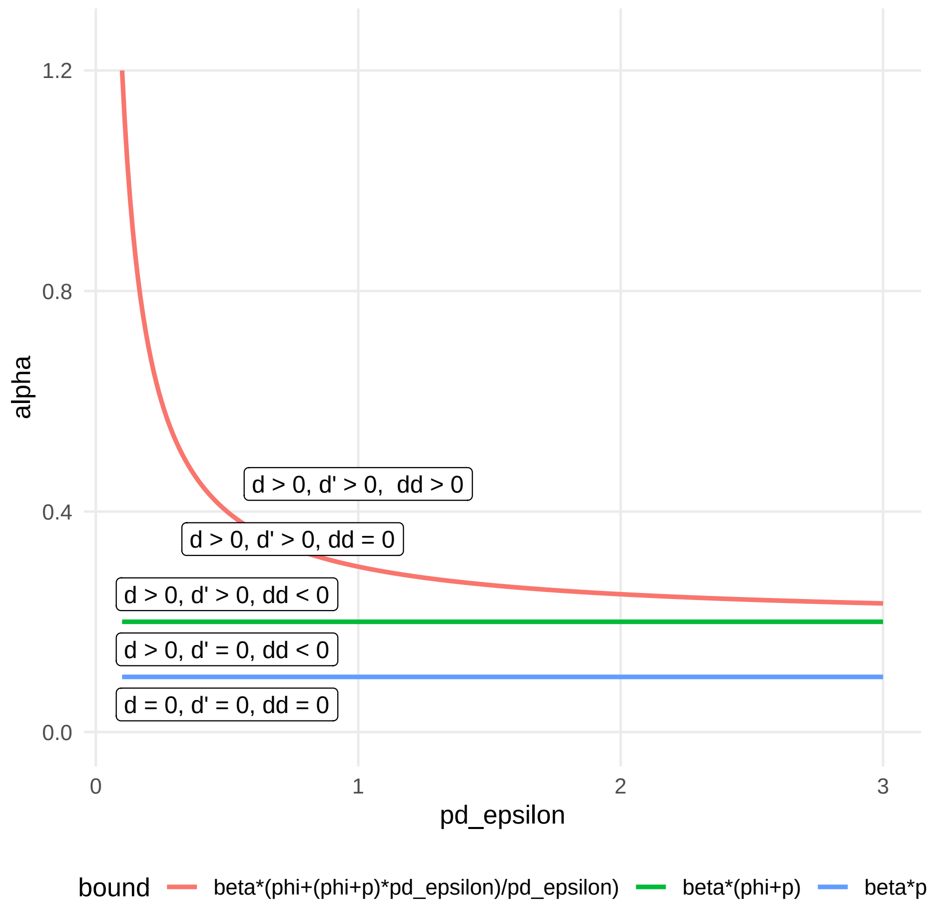

Figure 6: Call response by tie strength and information shock. d is duration with no social unrest, d' is duration with social unrest and dd is the difference in duration. pd_epsilon is the $\%\Delta\epsilon_{ijt}$ and alpha is α_{ij}. Assumes values of $\phi_{it} = p = 0.1$ and $\beta = 1$.

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 7 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 10 holds.[17] Given

[17]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

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, we provide more discussion about factors that likely shape how information flows across the networks represented in our CDRs and how information shocks may be differentially transmitted across this network. Three factors in particular are noteworthy and described in detail in this section. First, edges where the alter is is more central in this network from the perspective of information diffusion will experience more significant information shocks in the wake of social unrest than those with lesser centrality in the network. Second, edges where the alter's information is more differentiated from the ego's may also have higher information shocks. This might be the case when the two share few common friends may different information diffused to them. Third, individuals whose daily lives and routines bring them into close proximity to localized social unrest likely know more about what is happening on the ground and thus experience a greater information shock as a result of this unrest.

3.5.1 Diffusion Centrality

Following 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.

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.

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.[18]

King (2020) presents three additional concepts that refine diffusion centrality: *word-of-mouth*, *obstructed*, and *visibility* centrality.[19] 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.[20]

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

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

$$\mathbf{H}(\mathbf{D}, S) = \sum_{s=1}^{S} \mathbf{D}^s \tag{14}$$

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

$$NG(\mathbf{D}, S)_j = H(\mathbf{D}, S)_j. \tag{15}$$

[19]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.

[20]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.

(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.[21] 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 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.*

[21]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.

(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

We use a difference-in-differences style 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 assumptions 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:

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

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

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

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

$$y_{ilt} = \alpha_i + \gamma \text{Episode}_{lt} + \delta \, \text{Unrest}_{il} \times \text{Episode}_{lt} + \epsilon_{ilt} \tag{18}$$

However, a non-absorbing treatment is not the only wrinkle we face in estimating our parameter of interest. Our context features staggered social unrest as well, which has implications for the estimation of treatment effects when there are dynamic treatment effects or when treatment is heterogeneous (Goodman-Bacon, 2019; de Chaisemartin and D'Haultfœuille, 2020).

Goodman-Bacon (2019) states the need for robust estimators of difference-in-difference study designs very clearly. The weighting of the TWFE coefficient is weighted average of different treatment effects. In a simple "early and late" treatment model (i.e., group 1 is treated earlier, group 2 later, group 3 not at all), this can be expressed as the weighted sum of four treatment effects (or comparisons). These are: early v. untreated, late v. untreated, early v. late, before treatment and late v. early group after treatment. This last effect is important: groups who were already treated may act as controls even after they have received treatment. In the context of our event-only DiD, and TWFE estimator, this would create similar comparison groups where people faced with unrest at a later date would be compared to those who face *ongoing* unrest.

Moreover, weights are often unreasonable. First, weights on these cell specific treatments are sometimes negative, which could result in a treatment effect that is opposite in sign from a cell specific effect. Second, groups treated mid-panel receive higher treatment weights, despite the lack of any theoretical reason why this would be the case.

In addition to demonstrating the issue of negative wights, de Chaisemartin and D'Haultfœuille (2020) demonstrates a related issue when heterogeneous treatment effects are at play. In particular, even when all weights are positive, if there is significant heterogeneity in the treatment effects of different groups, it is possible that that average of these group level treatment effects could be opposite the sign of the TWFE estimate. This brings our attention back to the weights generated by TWFE because they are not informed by theory, but rather an artifact of the estimator. Thankfully, the authors provide two tests that can be used to diagnose the potential for these issues and a new estimator, DID^M, appropriate for estimating the ATE in our context. This approach is robust to issues brought on by variable treatment timing, heterogeneous, and dynamic effects. Finally, their approach is a rare estimator in the family of difference-in-differences that not only allows for treatment to turn "on" and "off," it naturally estimates the effect of entering and leaving treatment to construct the treatment effect estimate. However, these feature are bought with a number of assumptions, which we will describe in the next subsection.

4.2 DID^M Estimator

The DID^M estimator is the weighted sum of the group level differences that arise when groups move in or out of treatment. A number of conditions and assumptions need to hold for DID^M to deliver valid estimates of the treatment parameter. Three of these conditions involve restrictions on the data structure and can be directly verified. First, the dataset must feature a balanced panel of groups, as ours does. Second, treatment must be sharp within these groups. That is, all individuals in a group must have the same treatment status. In this case, this is a matter of construction. we construct groups based on their most used tower in order to ensure groups are non-overlapping. Third, the data features stable groups to serve as comparisons for those who switch treatment statuses. That is, when tower enters treatment there exists another that remains untreated in both periods, and vice versa. We check this in the data and find that there are always untreated groups to compare to when a tower moves into treatment and exists groups which remain treated in some periods where social unrest lapses.[22]

Another five assumptions cannot be directly verified. The first two assumptions involve strong exogeneity. In particular, for the contribution to the ATE of those who join treatment to be identified, strong exogeneity must hold for control towers.[23] For example, this condition forbids cases where protest or other social unrest occurs because of another shock specific to this location at this time. Likewise, the contribution to the ATE of those who leave treatment depends on the same condition for treated towers – social unrest cannot lapse because of another shock.[24] The next two assumptions involve the parallel trends assumption, which remains crucial as it does in standard DiD. Again we consider symmetric assumptions for the identification of contributions of those who join and those who leave treatment. For those who join treatment, the standard common trends assumption applies, That is, for $t \geq 2$, $E(Y_{l,t}(0) - Y_{l,t-1}(0))$ does not vary across l and particularly across groups who are treated and are not. Note that this assumption does not admit anticipation effects, a fact that drives us to omit protest from our measure of treatment with social unrest. Additionally, we document these pre-treatment trends in section 5.1. Likewise, for those who leave treatment we invert this common trends assumption to consider common trends among treated areas.[25] Because of our short windows of treatment, however, it is difficult to provide suggestive evidence around the plausibility of this assumption. Finally, our last assumption to establish causality is a mean independence assumption. More specifically, we assume mean independence between a group's outcome and other groups treatments. This assumption serves to exclude spillovers from social unrest.[26] While we cannot test this assumption,

[22]Where there are not stable treatment groups to estimate the movement of an area out of treatment, this data does not contribute to the estimator.

[23]In technical terms, this means that where l is group and t is time, for all $(l,t) \in \{1,\ldots,L\} \times \{2,\ldots,T\}$, $E(Y_{l,t}(0) - Y_{l,t-1}(0)|D_{l,1},\ldots,D_{l,T}) = E(Y_{l,t}(0) - Y_{g,t-1}(0))$.

[24]Similarly, we can write For all $(l,t) \in \{1,\ldots,L\} \times \{2,\ldots,T\}$, $E(Y_{l,t}(1) - Y_{l,t-1}(1)|D_{l,1},\ldots,D_{l,T})$ $= E(Y_{l,t}(1) - Y_{g,t-1}(1))$.

[25]That is, we assume that for $t \geq 2$, $E(Y_{l,t}(1) - Y_{l,t-1}(1))$ does not vary across l.

[26]Formally, for all l,t, $E(Y_{l,t}(0)|\mathbf{D}) = E(Y_{l,t}(0)|\mathbf{D}_g)$ and $E(Y_{l,t}(1)|\mathbf{D}) = E(Y_{l,t}(1)|\mathbf{D}_g)$.

we are able to document by analyzing the sensitivity of treatment effects to the distance at which a tower becomes treated.

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.

4.3 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. Despite this, we can at least provide evidence around these issues by building a restricted subsample of only those who tend to use largely voice or SMS services and less data than one would need to utilize a smartphone.

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.

4.4 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.

4.4.1 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.

4.4.2 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 justice to the areas outside of Port-Au Prince. Using this logic, we filter cellphone towers to be within the greater PAP region.[27] Next, we match these towers to protest events that happened within one kilometer

[27]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

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. Finally, we assign treatment status to an individual if an unrest event happened at their most used tower. To record a proxy for mobility, we compute both the HHI of call distribution among towers and the share of calls at the most used tower.

4.4.3 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

du Jong, Martissant, Morne L'Hopital, and Turgeau.

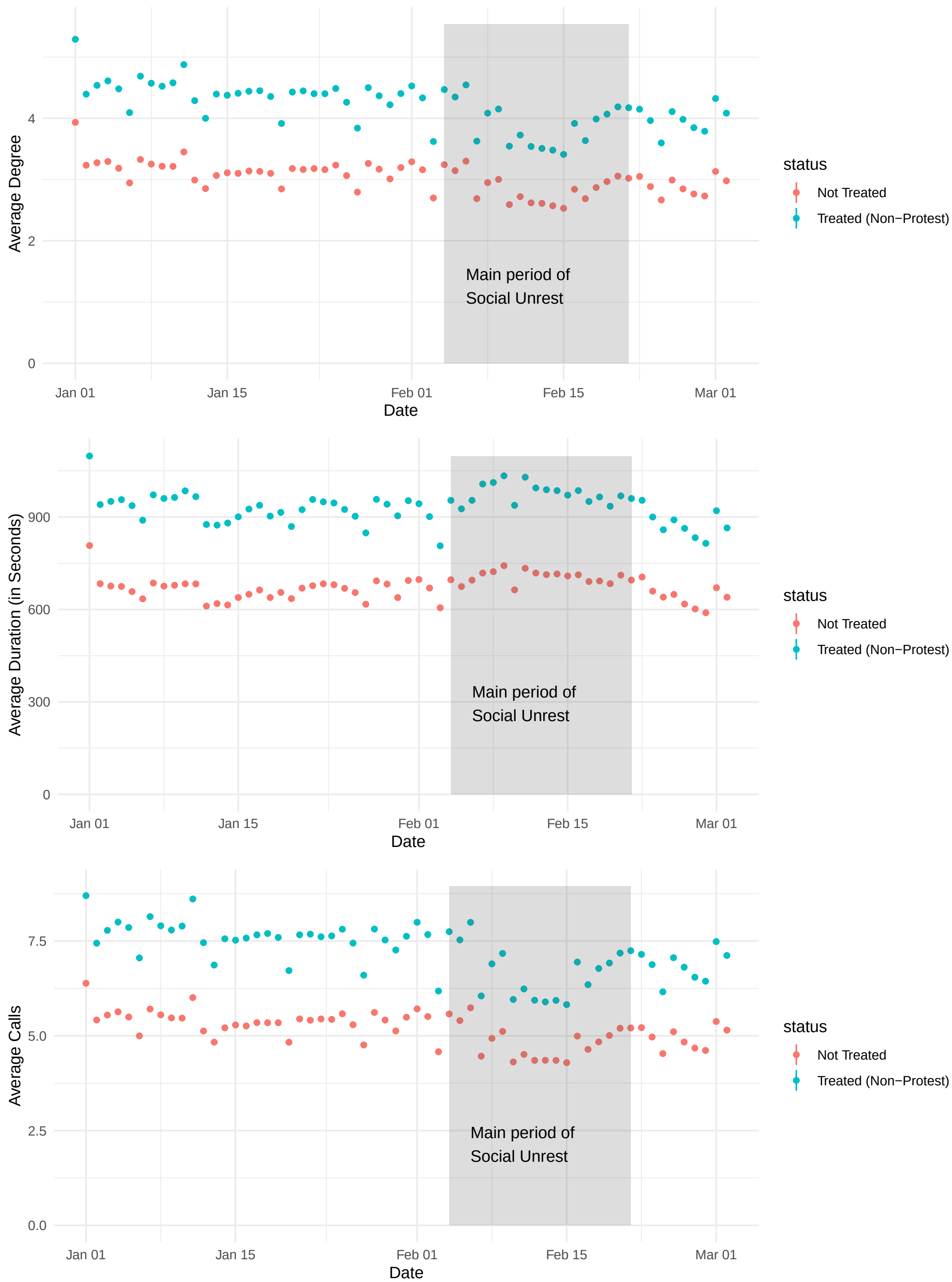

Figure 7: Average degree, duration, and calls over the sample period by exposure to non-protest social unrest event.

not drop calls or texts to those outside of PAP.

4.4.4 Estimation and Standard Errors

All estimates are obtained in R. All fixed effects specifications are estimated in R using the command felm from the lfe package. For fixed effects specifications, standard errors are clustered at the tower level (multiple antennas in the same place are considered part of one tower). The choice of clustering variable follows from the design based approach in Abadie et al. (2017), since treatment is assigned by location of the most used tower. DID^M is estimated using the command did_multiplegt from the package DIDmultiplegt. For DID^M, standard errors are computed using a block bootstrap with tower as the clustering variable (500 repetitions). Finally, diagnostic tests of the TWFE weights are performed using the command twowayfeweights from the package TwoWayFEWeights.

5 Results

5.1 Pre-Treatment Trends

To provide qualitative evidence about the plausibility of the pre-trends assumption, we visualize our data over the two month study period. Figure 7 plots the averages of outcomes by exposure to non-protest social unrest events. To demarcate the most intense period of social unrest, we shade the area after which the number of social unrest incidents spiked in Port-Au-Prince. During this period embassy reports increased in severity from “Avoid Area” to “Home Restriction” and “Shelter in Place.”

A number of patterns within the pre-trends are interesting. Usage is higher among those in areas that were ever treated, suggesting that these social unrest events were associated with some feature of the area. It is difficult to say exactly what drives this, though proximity to roads or gathering spaces, which tend to be used for commerce. For the three outcomes, we see reductions in calling on Saturday and Sunday. This is most pronounced when considering degree or calls,

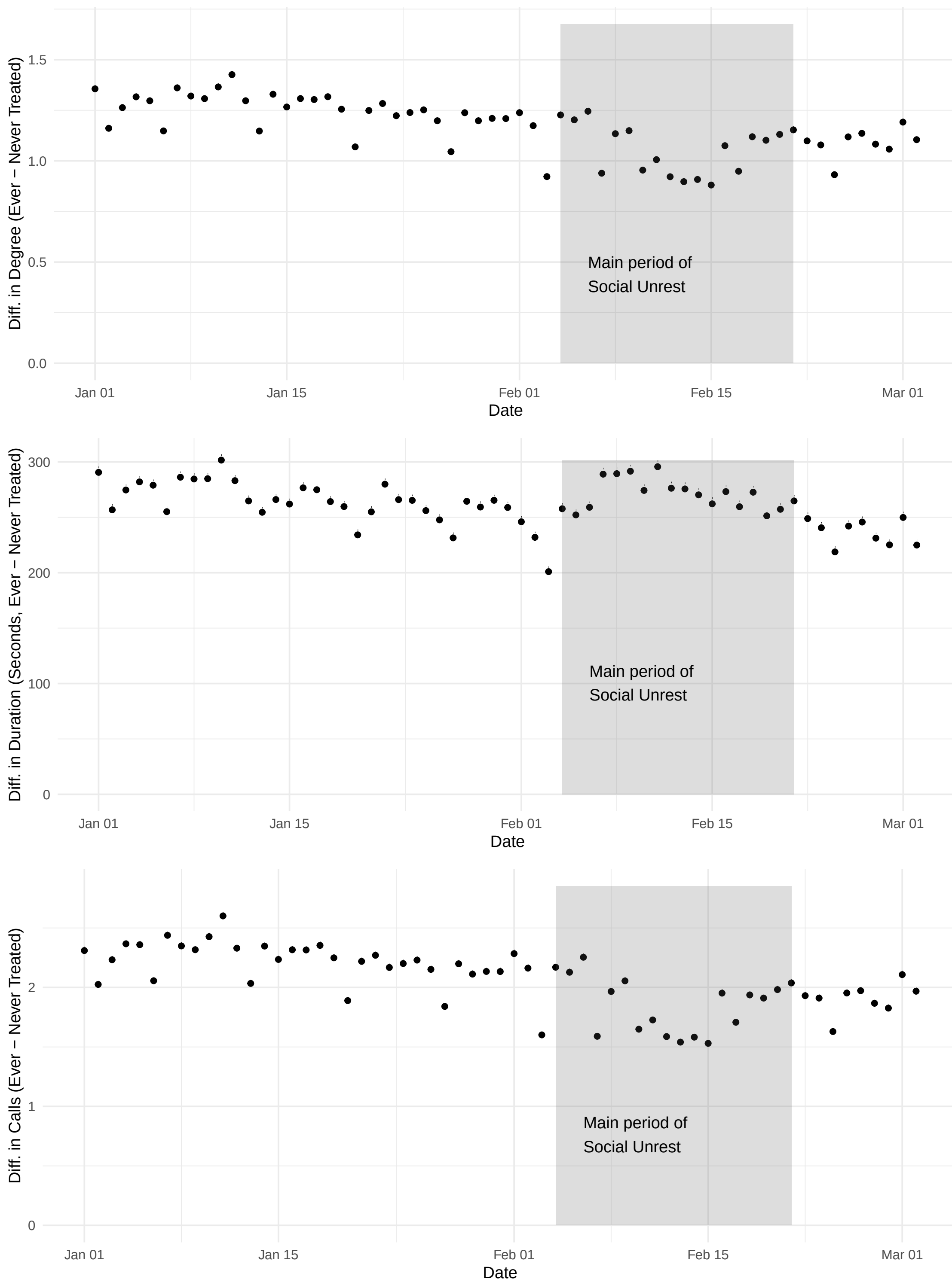

Figure 8: Differences in degree, duration, and calls over the sample period by exposure to non-protest social unrest event.

and less pronounced when considering duration. However, calling behavior follows remarkably similar trends between areas where non-protest social unrest took place and those where it did not.

Similar figures are included in the appendix for two other definitions of treatment. First, figure 14 presents these same outcomes by exposure to protest. Second, figure 15 presents the outcomes by exposure to any type of social unrest (protest or non-protest). Qualitative conclusions from inspection of these figures is broadly similar. Notably, however, including all social unrest events in treatment magnifies the difference int pre-trend outcomes as compared to the other two definitions.

While formal tests of pre-trends are often undertaken, such tests can further bias conventional estimates when the pre-trends assumption is violated (Roth, 2019). Therefore, we opt not to report pre-trends tests until we are able to account for the distortions from pre-testing in our estimates.

5.2 Main Effects: Non-Protest Social Unrest Events

5.2.1 Diagnostic Tests of the TWFE Estimator

To diagnose robustness of TWFE to heterogeneous treatment effects, we run two tests outlined by de Chaisemartin and D'Haultfœuille (2020) in Corollary 1. We run these tests under a common trends assumption, using our non-protest social unrest variable as treatment and degree, call weighted degree, and duration weighted degree as outcomes. Because of the computational expense of the DID^M estimator, we run these tests on a subsample of 100000 members of the population, and over five weeks, beginning the 21st of January until the 24th of February. For all three outcomes, we find similar results when characterizing the weights of TWFE. All ATTs estimated by TWFE are assigned positive weights, and therefore, the sum of the positive weights is equal to 1. This result eliminates one issue that we commonly test for, which is that the TWFE coefficient could plausibly be of a different sign than all of the ATTs. However, the estimate produced by is still compatible with a data generating process where the average of those ATT is equal to 0, meaning changes in weights could lead to reversals in the sign of the treatment effect.

Table 3: Effects of Social Unrest on Network Degree

	Degree (Total Contacts)		
	(1)	(2)	(3)
	DiD	TWFE	DID^M
Episode of Non-Protest Social Unrest	0.021	-0.085^{***}	-0.048^{***}
	(0.031)	(0.025)	(0.012)
Ever Non-Protest Social Unrest	0.259^{**}		
	(0.102)		
Day FE	Yes	Yes	
Indv. FE	No	Yes	
Cluster	Tower	Tower	Tower†
$N \times T$	3,067,920	3,067,920	3,067,920
R^2	0.005	0.648	
Adjusted R^2	0.005	0.638	
Residual Std. Error	5.094	3.071	
df RSE	3,067,882	2,982,664	
N effect			1,065,149
N switchers effect			181,124

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
† Block bootstrap with 500 repetitions

This suggests there is reason to be concerned about the TWFE weighting, given the fact that the TWFE estimator yields weights that may be arbitrary.

5.2.2 Comparison of Estimators

We estimate treatment effects using the DiD, TWFE, and DID^M on a common subsample of 100000 users over five weeks, beginning the 20th of January until the 24th of February. Using both the TWFE estimator and the DID^M estimators, we see that while the number of contacts and calls per day falls, duration spent conversing does not. In particular, using duration is positively but insignificantly impacted whereas using DID^M duration is negatively impacted but still insignificant. Therefore, based on these results, we conclude that total duration remains similar to before.

Table 4: Effects of Social Unrest on Total Calls

	Total Calls		
	(1)	(2)	(3)
	DiD	TWFE	DID^M
Episode of Non-Protest Social Unrest	0.031	-0.153^{***}	-0.103^{***}
	(0.054)	(0.050)	(0.024)
Ever Non-Protest Social Unrest	0.471^{***}		
	(0.173)		
Day FE	Yes	Yes	
Indv. FE	No	Yes	
Cluster	Tower	Tower	Tower†
$N \times T$	3,067,920	3,067,920	
R^2	0.005	0.617	
Adjusted R^2	0.005	0.606	
Residual Std. Error	9.753	6.141	
df RSE	3,067,882	2,982,664	
N effect			1,065,149
N switchers effect			181,124

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
† Block bootstrap with 500 repetitions

Despite the concordance in sign between the DID^M estimates and the TWFE estimates on contacts and calls within this sample, we get estimates that differ in magnitude across these estimation methods. While coefficients are on the same order of magnitude, the differences in results to matter. Taking the DID^M estimates as the true effect, we see bias in the TWFE estimates for contacts and calls on the order of 48 and 77% of the size of the DID^M coefficients. Likewise, the coefficient on duration switches signs when moving from TWFE to DID^M. Theses difference should reflect the differences in weighting between the TWFE and DID^M estimators. Given the known problem with TWFE weights when treatment effects are heterogeneous or treatments are staggered, we should prefer the weighting for the the DID^M estimator which is intentional as opposed to arbitrary. Therefore, given these differences, we select DID^M as our preferred estimator.[28]

5.2.3 Estimates and Interpretation of Causal Effects

Using DID^M we estimate episodes of social unrest reduce degree by 0.048 contacts, reduce calls by 0.103, but do not spend significantly less time talking on the phone. Considered another way, individuals spend *more* time talking to the contacts who they do contact in periods of social unrest: the reduction in contacts amounts to a roughly one percent of average daily contacts over the period, while the (insignificant) reduction in duration is about one quarter of one percent.

Notably, the reduction in number of contacts is consistent with our hypothesis from the model that people cease communication with those with whom they have weak ties. While the formal model does not take a stance on node level duration, our hypotheses, based on assumptions about the size of informational shocks, suggested we should see an increase in duration for those treated with social unrest. These results are therefore inconsistent with our hypothesis but not the formal model overall.

Interestingly, this pattern of result bears resemblance to results in related contexts. Romero et al. (2016) considers the metadata of text messages sent in a hedge fund during price shocks, using a form of TWFE to estimate that network structure becomes more tightly knit in the face of such shocks.[29] Likewise, Blumenstock et al. (2016), finds that after a large earthquake in Rwanda calls and airtime transfers are made to those in the affected area. In particular, transfers are made between pairs of individuals with histories of reciprocal favor exchange. Finally, using Jia et al. (2021) finds that after an earthquake in the Yu'an province, calls are more likely to be made to those in their family when families were closer knit. Like in those settings, this pattern of results might imply people interacting more to their close or reciprocal contacts.

[28]One other note about DID^M. When errors are homoskedastic and uncorrelated, TWFE may yield a lower variance estimate even though it is biased. Thus there would be a bias-variance trade-off between TWFE and DID^M. While our errors (and treatment) are correlated, this bias-variance trade-off does not play out in our case. In particular, DID^M sees smaller standard errors in some cases.

[29]While users are facing stress as well, our setting clearly differs in that most cellphone users will not feel culpable for previously made decisions when social unrest strikes. Hedge fund employees on the other hand may need to wrestle with assignments of blame if losses are accrued during such price shocks.

Table 5: Effects of Social Unrest on Total Call Duration

	Total Duration (in seconds)		
	(1)	(2)	(3)
	DiD	TWFE	DID^M
Episode of Non-Protest Social Unrest	36.813***	9.974	-4.448
	(9.088)	(6.282)	(6.990)
Ever Non-Protest Social Unrest	87.738***		
	(21.979)		
Day FE	Yes	Yes	
Indv. FE	No	Yes	
Cluster	Tower	Tower	Tower†
$N \times T$	3,067,920	3,067,920	
R^2	0.001	0.507	
Adjusted R^2	0.001	0.493	
Residual Std. Error	1,819.503	1,295.769	
df RSE	3,067,882	2982664	
N effect			1,065,149
N switchers effect			181,124

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
† Block bootstrap with 500 repetitions

However, the precise zero on duration also raises another possibility of a nuance that departs modestly from the theoretical model we have presented earlier. In particular, if budget constraints bind or it is not possible to obtain airtime credit or visiting an airtime vendor, it may be that there is a process of substitution taking place around events of social unrest. That is, while similar to the story above, the move from very weak ties to stronger or more informed ties is navigated via a budget constraint.

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. Consistent with a model of calling during social unrest, we find that network degree falls along with the number of calls made while the duration of time spent talking remains constant. These results paint a story where people reach out their close friends (or their close friends reach out to them) when their neighborhood is the sight of social unrest.

6.2 Future Work on Network Response

6.2.1 Further Tests of Model Hypotheses

While these results paint a picture consistent with our theoretical model, more extensive testing of the model hypotheses is needed. First, we see to provide evidence around tie strength. To do so, we will restrict degree to only those alters who are strong ties, as defined earlier. If we find larger (more positive/less negative) coefficients on social unrest in this construction of these outcomes, this provides evidence around

While we expect that very weak ties may not be contacted, weak ties who are well informed might be (Granovetter, 1973). To further test this hypothesis, we will estimate the same models with outcomes constructed using only alters who are high degree ("informed") weak ties. This may give us a sense of if the "strength of weak ties" in this context. In addition, we can compare this to a number of other restrictions on the outcome variable to test effects in other similarly defined subgroups.

Finally, we might also want to test the second order effects of social unrest on calling, to document the potential for diffusion within these contexts. To do so, we can estimate the treatment effects of second order connections of those treated with social unrest on the day of those episodes.

6.2.2 Further Tests of Robustness

First, while we have a large and random sample of the population of interest, testing the same hypotheses in additional subsamples could provide differences in results due to sampling error. Ideally, we would not need to sample at all, though the DID^M is very memory intensive, thus requiring it. However, we are able to use substantially larger samples when only computing the TWFE estimator, potentially even a full sample. Therefore this could serve as a measure for how much these individual samples differ from the population sample.

Second, to further assess pre-treatment trends, de Chaisemartin and D'Haultfœuille (2020) provides a placebo estimator which constructs placebo treatment effects from the time periods just before individuals switch into treatment, therefore testing for pre-pretends. Additionally, Roth (2019) presents methods of testing pre-treatment trends and then accounting for this within the main specification.

Third, we may want to account for heterogeneity in treatment effects via mobility of cellphone users. Using baseline estimates of tower diversity and call share at their primary tower, we can characterize the importance of mobility on the results at hand. Using these results, we may be able to address some attenuation that results from our method of assigning treatment.

Fourth, while we define treatment as non-protest social unrest episodes, it would be interesting both to consider descriptive measures of treatment for all social unrest events, and protest only. Given placebo tests discussed earlier and the DID^M estimator, we can then assess how crucial our treatment definition is. While we suppose that protests are anticipated, the placebo estimator could provide evidence for or against this.

Fifth, to better understand treatment assignment, we may also want to vary the distance from tower to social unrest by which the tower becomes treated. In particular, we will construct an alternative definition of treatment where only towers within a smaller radius of social unrest are considered treated. Additionally, this could serve as a source of heterogeneity in treatment. For example, if calling behavior differs between those who are directly next to social unrest as compared to those who are at a safe distance, characterizing these differences might be interesting.

Sixth, all of these outcomes could be similarly computed with alternative measures of the network. In this paper communication networks, and more specifically call networks, serve as a proxy for social networks. Other measures of communication are available, most notably SMS networks. Future work might investigate these SMS networks using similar approaches. Likewise an analysis of data usage might give clues about the use of alternative calling or messaging services including WhatsApp or Facebook. Similarly the recent outage in WhatsApp servies might serve as an interesting setting to study the relevance of these services on network measurement using communiations networks.

6.3 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.[30] 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.

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

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A Additional Figures

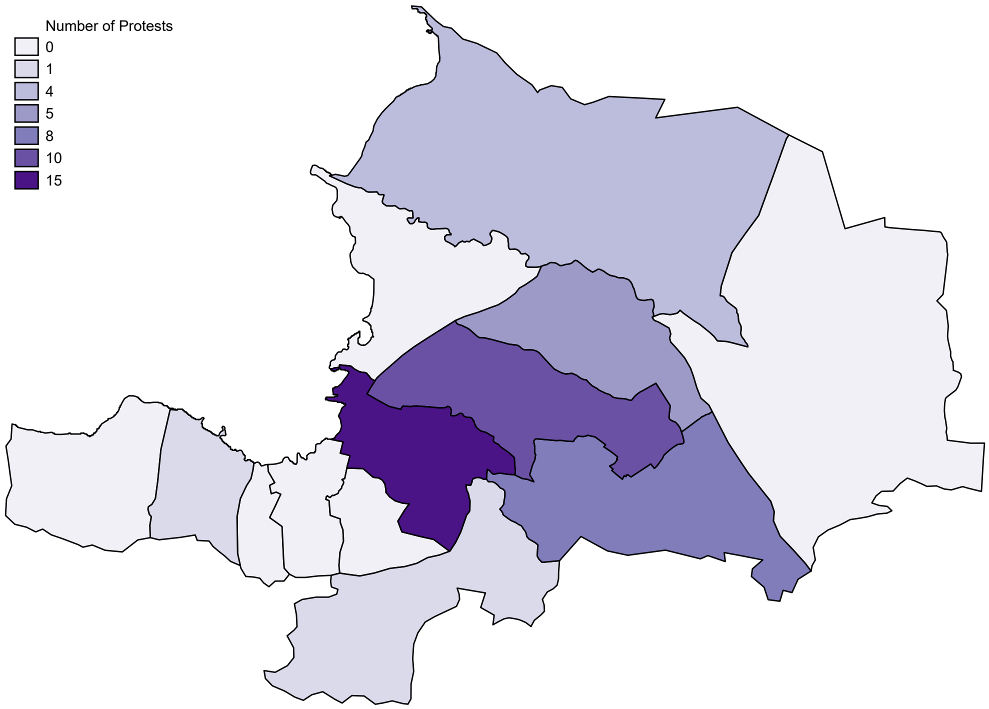

Figure 9: Protests in Port-au-Prince, January and February 2019.

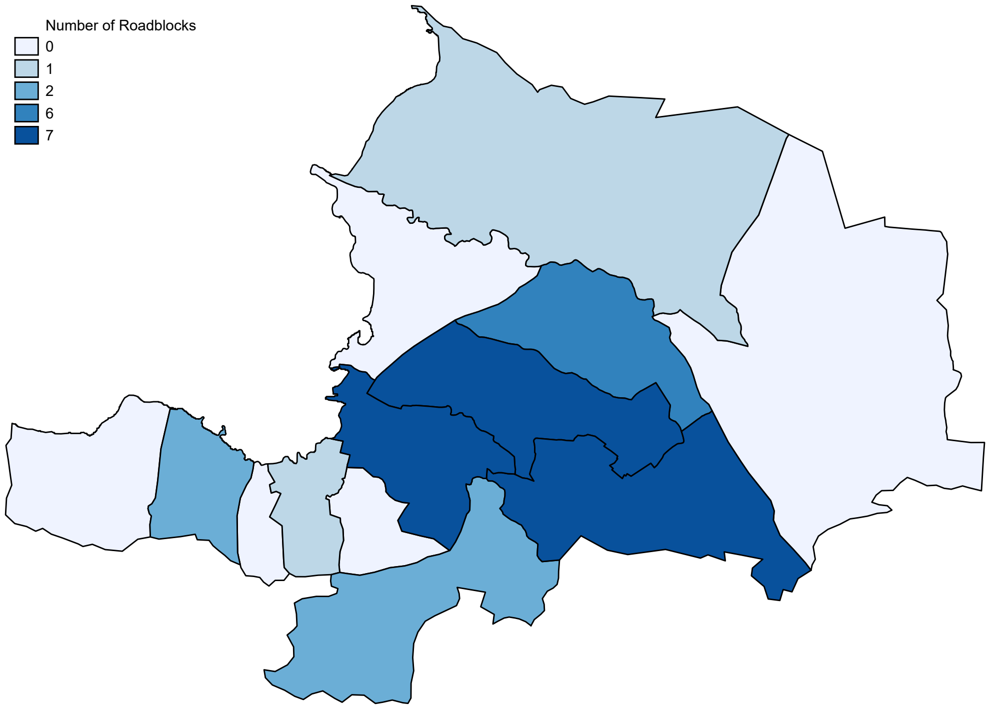

Figure 10: Roadblocks in Port-au-Prince, January and February 2019.

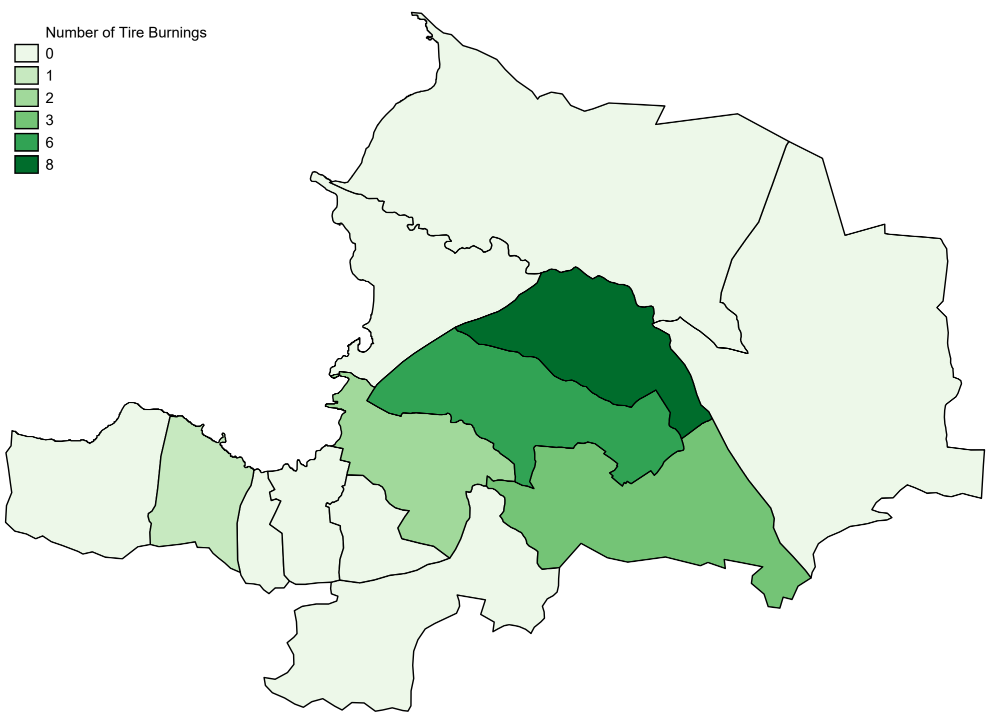

Figure 11: Tire Burning Events in Port-au-Prince, January and February 2019.

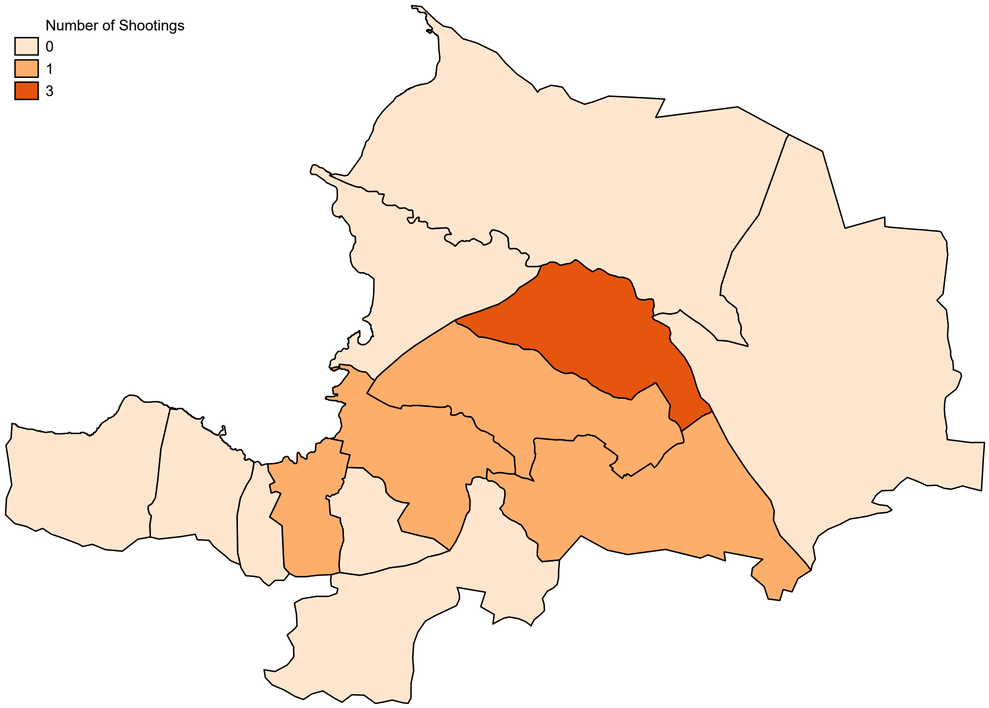

Figure 12: Shootings in Port-au-Prince, January and February 2019.

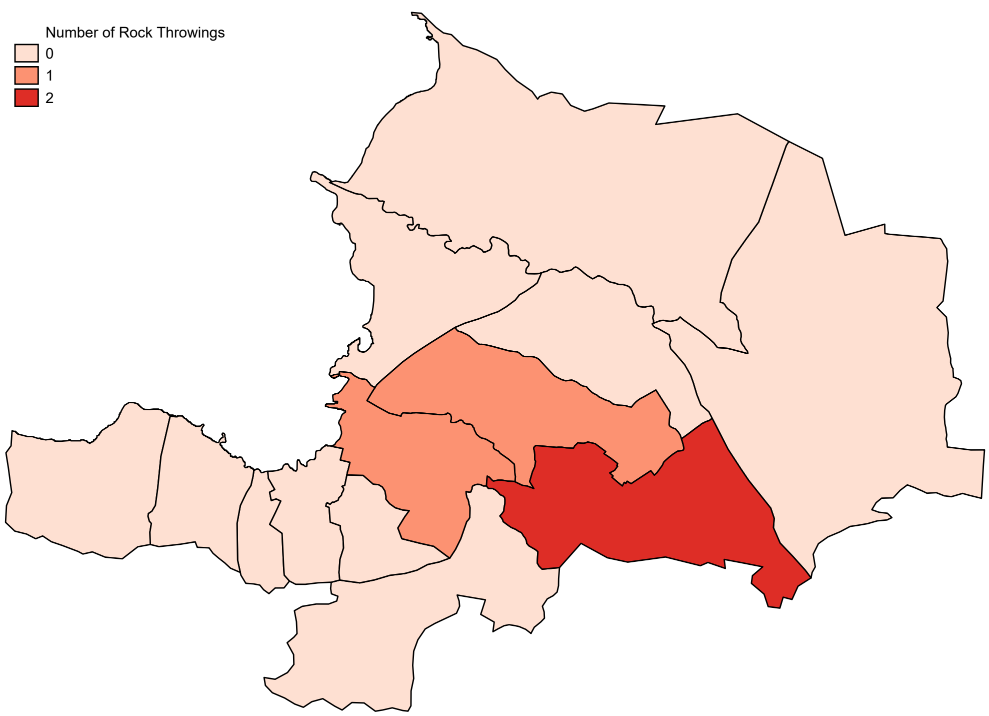

Figure 13: Rock Throwing Events in Port-au-Prince, January and February 2019.

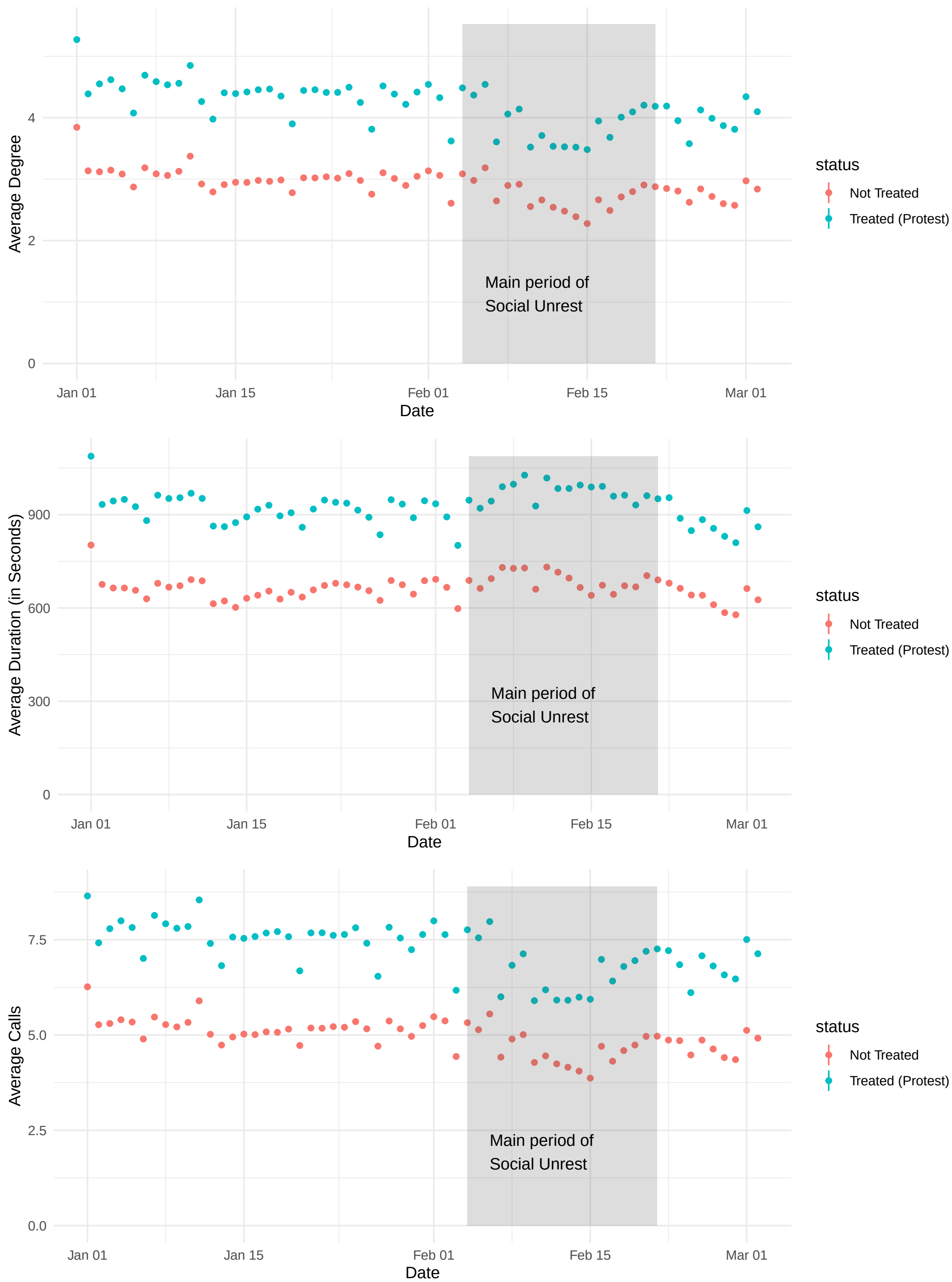

Figure 14: Average degree, duration, and calls over the sample period by exposure to protest.

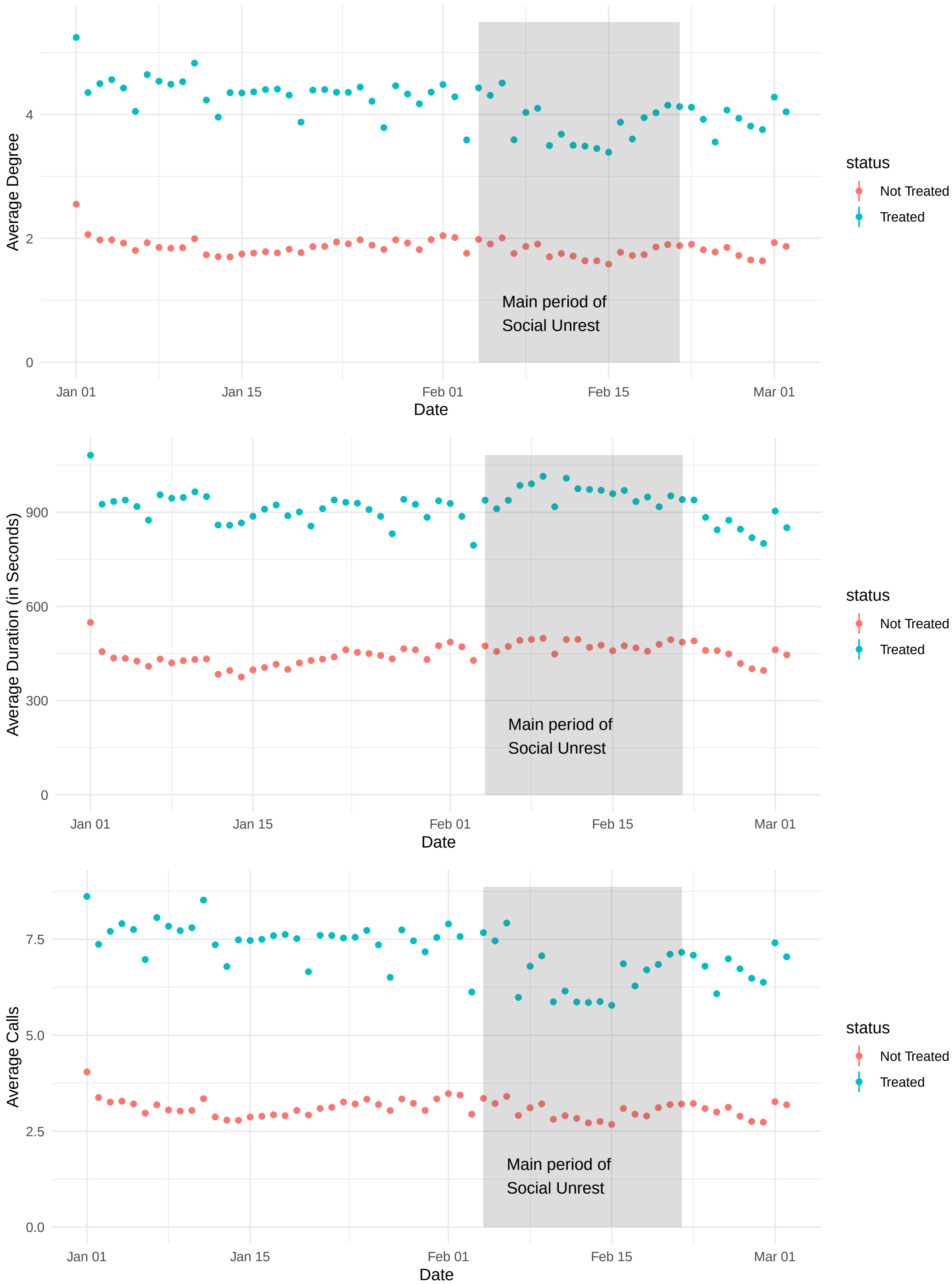

Figure 15: Average degree, duration, and calls over the sample period by exposure to any form of social unrest.

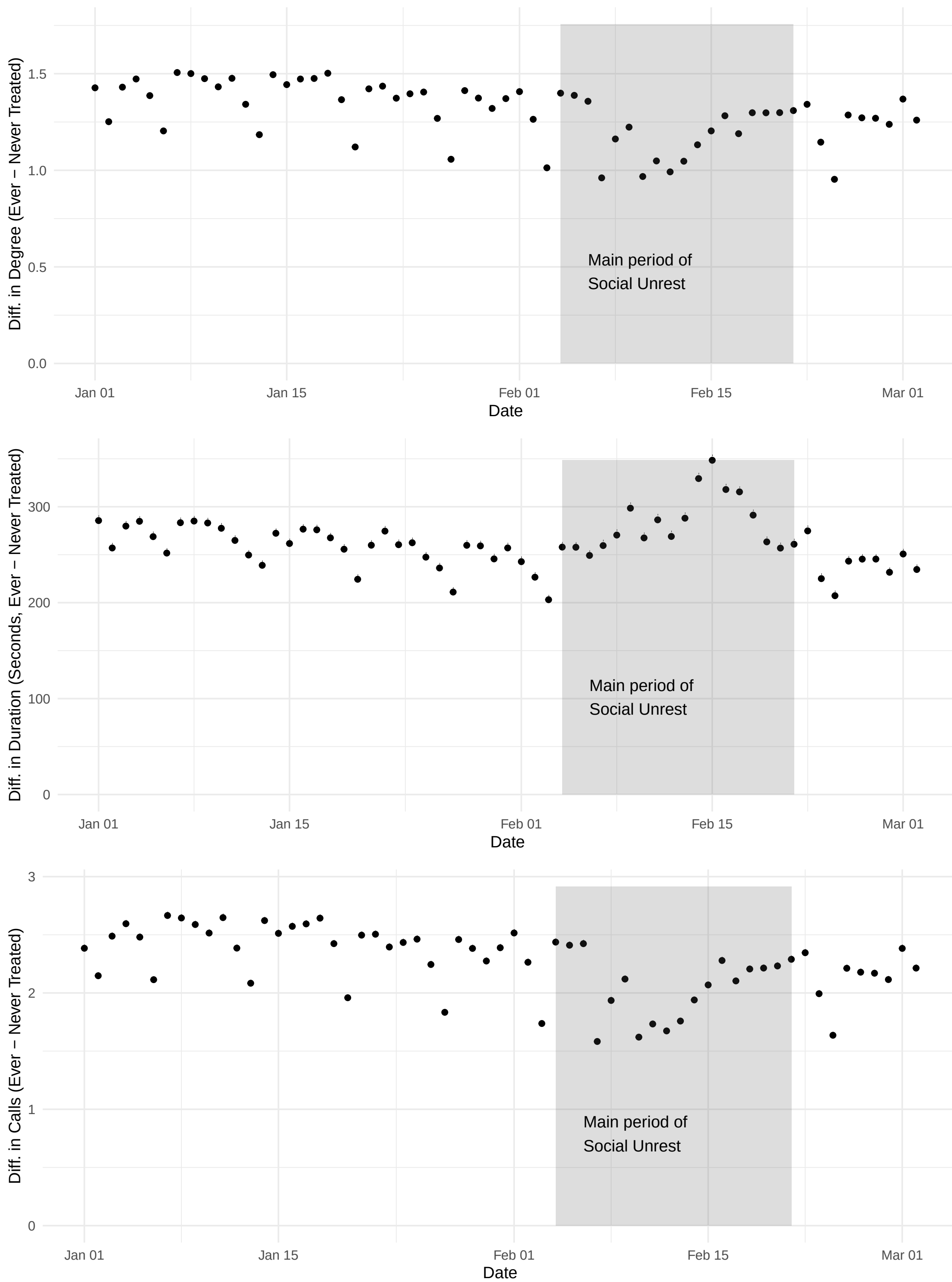

Figure 16: Difference in degree, duration, and calls over the sample period by exposure to protest.

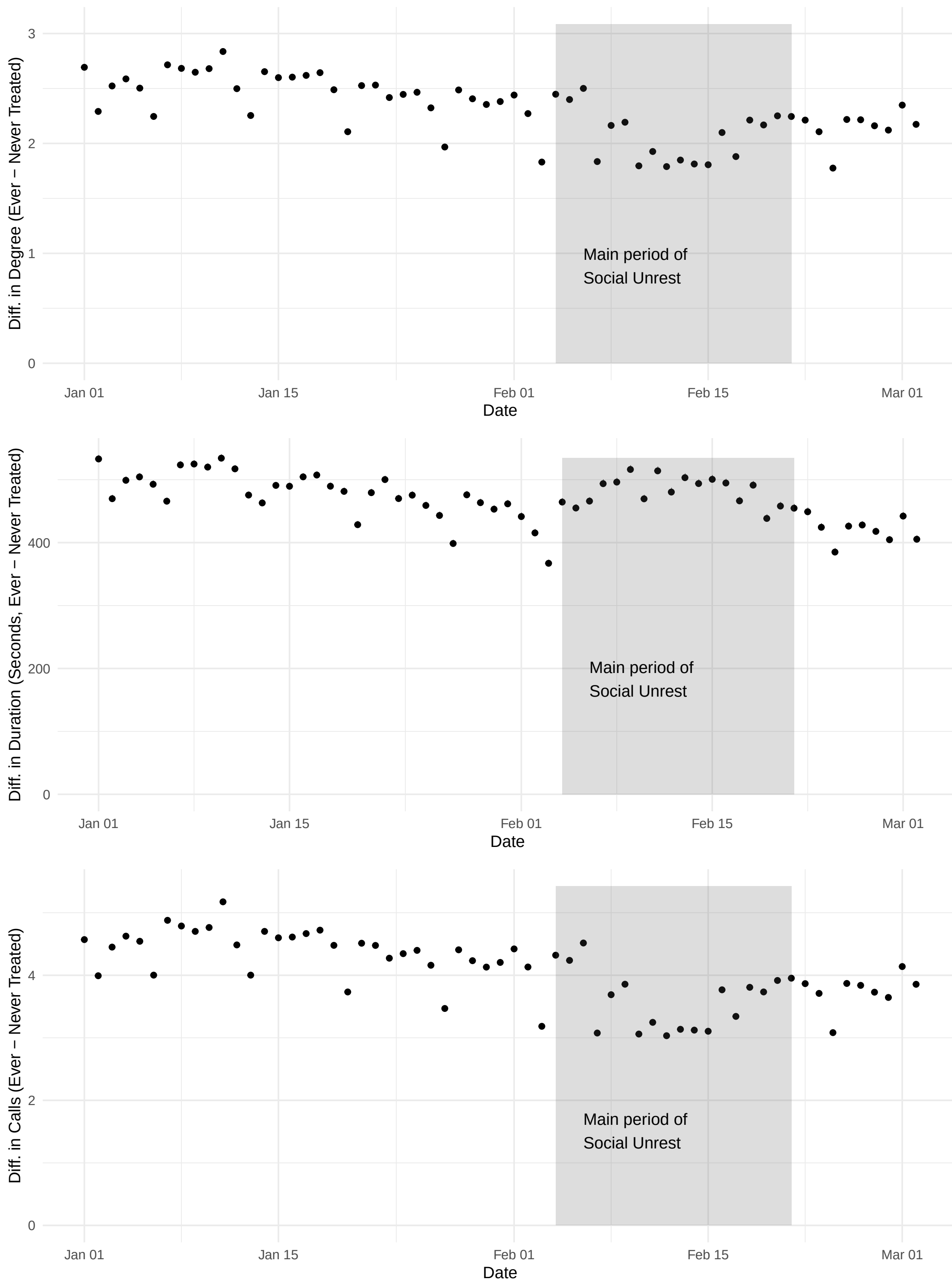

Figure 17: Difference in degree, duration, and calls over the sample period by exposure to any form of social unrest.