Port-Au-Prince Calling: Social Network Response to Social Unrest using Mobile Phone Metadata in Haiti*

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Abstract

Which connections do people value most in times of crisis? We examine a period of social unrest in Haiti to understand how social networks respond to social unrest. We construct communication networks using mobile phone metadata from a major mobile network operator in Haiti and a detailed geo-referenced timeline of severe unrest. These episodes are geographically isolated, persist for a matter of days, and vary in their degree of coordination and predictability. We use the more spontaneous of these events to estimate how calling behavior responds day-to-day. Estimating treatment effects using a difference-in-differences estimator robust to variation in treatment timing with heterogeneous treatment effects, we find that daily contacts decrease, but total talk time remains constant. These results are consistent with predictions from a theoretical model of social network response to social unrest. However, the number of daily contacts with network neighbors who are strong ties and have low degree does not fall during the period of social unrest, in contrast to other subgroups. This finding suggests a pattern of checking in on close friends, family or other associates in lieu of broader information search.

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

"When you are in trouble, you find out who your friends are." -Haitian saying[1]

This oft-cited saying in Haiti reflects the activation of social networks in response to crises. While friends, relatives, or neighbors might provide access to cash, credit, or other material aid through risk-sharing networks, social infrastructure does not end with such transfers; networks can also play the vital role of providing information as well as emotional and psychological support in these instances (Aldrich and Meyer, 2015). Such crises can come in many forms. Covariate shocks in the form of natural disasters like earthquakes and hurricanes can precipitate intense times of "trouble" across a wide swath of a population, but localized disruption due to protests, looting and civil unrest can be equally troubling albeit in a more isolated manner. With a focus on the latter, we aim to understand how troubling times trigger differential social network usage by altering communication incentives.

Haitians have ample opportunities to find out who their friends are, as this saying suggests. In addition to frequent and recent natural disasters, Haiti has been rattled by a steady stream of civil strife, only some of which is covered by international news media. 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.[2] This period included mass demonstrations, roadblocks, and forced the cancellation of Carnival events in both 2019 and 2020. While these acute unrest episodes inflicted far less permanent damage to physical infrastructure than natural disasters, they were no less disruptive in their immediate vicinity and constitute a cleaner shock to the demand for information that is not confounded by collateral damage to communication infrastructure.

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. While social and political movements, including protests and civil

[1]In Hatian Creole: "Se le ou nan male w'ap konn kiyes moun ki zanmi w." See, for example, the glossary of Déralciné and Jackson (2015).

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

unrest, have always leveraged social networks in order to motivate and mobilize individuals (Campbell, 2013), social networks are not only connected to social unrest through political mobilization.[3] As incentives shift in times of stress and disruption, individuals activate their social networks, connecting and communicating with links new and old. We aim to characterize a broader network that includes bystanders whose daily lives are disrupted by localized unrest, rather than focusing on communication among protesters and organizers. This broader inquiry evaluates how such bystanders tap their networks to cope with this greater uncertainty and the risk to life and property. In doing so, we leverage the digital trace data left behind by mobile phone calls made during these episodes of social unrest.

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 major shocks.[4] 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. Such informal spread of information about social unrest could similarly serve to mitigate the disruption caused by such unrest. Additionally, calling behavior during crisis is revealing in that it expresses who and what people value. Do those who face unrest in their neighborhoods turn outward for support and information, or do they restrict their communications to their close friends, family and associates?

A few prior studies document how ICT-mediated social networks are activated in 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 the strength of family networks affect the dynamics of responses within families.[5] Blumenstock et al. (2016) also leverage an earthquake in Rwanda and document the flow of assistance into affected areas through mobile communica-

[3]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).

[4]The decision of authoritarian governments to shut down the internet and mobile communications in order to stymie the organization of protesters and to avoid their live stream footage of events provides a dramatic example of the importance of such information. Such embargoes impose a hefty price on bystanders who lose a valuable communication tool at precisely the time they most need it.

[5]More specifically, they characterize family networks as stronger or weaker according to their common friends outside of their family plan.

tion networks in the form of airtime transfers. Romero et al. (2016) examines the effects of asset price shocks on the communication network between employees at a hedge fund, finding that information flowed less freely within the organization during these shocks. These studies feature settings where major covariate shocks unexpectedly affect entire populations. While these are devastating and costly shocks, they are blunt, one-off events that provide little geographic variation with which to identify social network responses. For that, more frequent and localized shocks are more useful.[6] We leverage acute and spatially-isolated spells of social unrest in Haiti to understand how uncertainty driven by social unrest activates ICT-mediated social networks. That is, we estimate the impact of these episodes of social unrest on social networks.

Our empirical strategy is three-fold. First, we propose to examine a spell of social unrest in Haiti in early 2019, leveraging acute and spatially isolated unrest as exogenous shocks to the value of mobile communication. In particular, we restrict our focus to January and February in the Port-Au-Prince area, a time and place that experienced a marked escalation of social unrest. We argue that these spatially isolated shocks serve as a natural experiment suitable for a modified difference-in-differences empirical strategy. Second, to limit issues with anticipation effects, we restrict our analysis to the least predictable events, excluding protests from our definition of treatment. Third, we estimate our treatment effects using the DID^M estimator presented in de Chaisemartin and D'Haultfœuille (2020), which is robust to variation in treatment timing with heterogeneous treatment effects and flexible enough to allow units to leave treatment.[7] This estimator yields instantaneous treatment effects of areas of Port-au-Prince fall into and out of spells of social unrest.[8] Using this empirical strategy, we estimate the network response using mobile phone metadata from a large telecommunications provider in Haiti. These ICT-mediated social networks yields census-like coverage without the prohibitive expense of in-person sur-

[6] One working paper uses a similar kind of variation to understand how firms' location decisions are shaped by violence in Afghanistan (Blumenstock et al., 2020).

[7] In particular, in such contexts two-way fixed effects (TWFE) estimators may be biased due to issues with weighting of group specific treatment effects (Goodman-Bacon, 2019; de Chaisemartin and D'Haultfœuille, 2020). By weighting we encompass both what comparisons are included in error (i.e., should have zero weights) and the issues of negative and arbitrary weights that occur as an artifact of TWFE.

[8] By instantaneous, we mean the treatment effect using the period just before and just after treatment

veys. Moreover, the fine grained temporal nature of these communication networks yields the possibility to look at short run changes in network usage in response to shocks. We aggregate network activity into a daily 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 tower.

To frame this empirical analysis, we first construct a theoretical model of network response to social unrest, building on work by Björkegren (2019). In this model, the effect on calling behavior depends on the underlying strength of social connection and peer information relative to the cost of calling, which we define as the price of airtime plus an attention cost.[9] The model predicts that the very weak ties will not be contacted, but that other ties will be contacted according to whether they are high information, strong ties, or some combination of the two. Using these prediction, we hypothesize that social unrest will increase the duration of calls as a result of their accompanying information shock, reduce communication with very weak tie contacts, and increase or decrease medium strength ties communication based on their proximity to the unrest events. Notably, this should reduce number of contacts on average.

Using a five weeks window, using DID^M we estimate that non-protest social unrest reduces contacts by 0.05 per day and total calls by 0.1 per day. However, total duration (i.e., time spent talking) stays roughly constant.[10] This pattern of results might suggests people talk with a smaller set of important contacts – consistent with the hypotheses of the theoretical model described above. To explore who people value in a time of crisis, we decompose these effects by whether contacts are strong ties or weak ties at baseline. Similarly, we decompose results by whether contacts have high or low degree at baseline, which we view as proxying for peer information. When we restrict to only low degree strong ties, there is no reduction in the number of contacts– in contrast the main result and the other subgroups. This suggest that people most value checking in on their closest friends, family, or associates as the uncertainty of unrest arises. Interestingly,

[9]Essentially, this is an opportunity cost from diverting limited attention away from monitoring one's surroundings.

[10]DID^M is our preferred estimator. We diagnose differences between TWFE and DID^M where these differences should be attributable to differences in weighting of heterogeneous treatment effects in a context with variation in treatment timing. 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).

this story is also consistent with evidence from disparate shocks such as earthquakes and stock crashes (Romero et al., 2016; Blumenstock et al., 2016; Jia et al., 2021). In contrast to past work, we are able to draw on spatial variation in order to provide evidence using a difference-in-difference framework and are able to avoid the impact on infrastructure often inherent in natural disasters.

Our results matter for policymakers who are facing crises such as natural disaster or sit within organizations that are exposed to financial shocks. While we hypothesize that major shocks might spur contact to high degree peers who might have better access to information about what is happening on the ground, our results are inconsistent with this kind of information search behavior. Such behavior might allow networks to make use of 'small worlds' properties to efficiently diffuse information. However, this might require people to reach out to central ties even when they are not as close of connections (Granovetter, 1973; Strogatz and Watts, 1998). Instead, we see that actors within these networks form silos, speaking less to people outside their close ties.[11] Our results are also related from the finding that social networks are optimized for reciprocal support (i.e., the exchange of favors) in contrast to the flow of information (Jackson et al., 2012; Blumenstock et al., 2019). In light of this, we hypothesize there is a double penalty in information diffusion in the wake of crisis: not only are network structures oriented toward support as opposed to the flow of information, but also that people do not value connecting with those in their network who might engender information flow. Where different populations are not equally well connected, outside of broad-based information campaigns, this could lead to cases some groups are much less informed about the risks posed by a crisis.[12] Such issues with informal information spread points to the importance of such information campaigns which may use use one-way SMS blasts, through crowd-sourcing platforms, or harness individuals' movements or activities as relayed by their mobile devices (Azid et al., 2015; See, 2019; Lu et al., 2012; Sakaki et al., 2010). This suggests that while there may be some value of private communication, a robust disaster response should not rely on word-of-mouth alone.[13]

[11]In the words of Romero et al., 2016, networks 'turtle up.'

[12]For a similar example from a public health crisis, Bennett et al. (2015) document evidence of learning in response to SARS in Taiwan where recent arrivals miss out on learning about the novel virus.

[13]Some past work points to the importance of social capital in disaster response (e.g., Aldrich and Meyer, 2015).

2 Background

2.1 Related Literature

2.1.1 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, the degree to which has been documented in a literature 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).[14] 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. While soem work has looked to explain mobile communication networks as an end to themselves,[15] others focus on what this data can tell us social network structure and activation For example, Blumenstock et al. (2019) finds a preference for interconnected mobile networks among migrants, where relationships are supported by common contacts. This echoes results from in-person social networks constructed around support and favor exchange (Jackson et al., 2012).

This doesn't necessarily provide evidence to the contrary. Indeed, it may be instructive of issues that arise when social capital is weak.

[14]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).

[15]See for example Björkegren (2019), which takes the value derived 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.

2.1.2 Social Networks and Resiliency

Work documenting the use of networks in resilience shocks tends to focus on risk-sharing networks. These in person networks are relevant in the wake of idiosyncratic shocks (Fafchamps and Lund, 2003; de Weerdt and Dercon, 2006; Ambrus et al., 2014) and digital networks in the wake of both idiosyncratic and covariate shocks (Jack and Suri, 2014; Blumenstock et al., 2016; Riley, 2018). However, some recent work has begun to document the response of communication networks to crises, and how this informal information can matter for response to such crises. Jia et al. (2021) assess mobile communication patterns in the wake of the 2013 Ya'an earthquake in China, paying special attention to how interconnectedness of family networks affect the dynamics of responses within families. They find that those families (defined by those on the same family plan) who have more out of family contacts in comment are more likely to contact each other shortly after the earthquake, as opposed to other contacts outside of the family structure. Romero et al. (2016) examines 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. They argue that response, affectionately described as 'turtling up,' represents a reduction in the "adaptiveness" of the network, negatively impacting the ability of the organization to gather information during such price shocks. Additionally some work also documents how these networks can aid in responding to crises. For example, Bennett et al. (2015) documents evidence of learning in response to SARS in Taiwan by comparing the behavior of recent migrants to others in the area. They interpret differences in preventative actions in response to local (as opposed to national information) as resulting from social interactions with peers.

2.1.3 Crises, Protests, and Diffusion of Information

Social networks are important in mobilizing political participation (Campbell, 2013; Bursztyn et al., 2021). 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 cen-

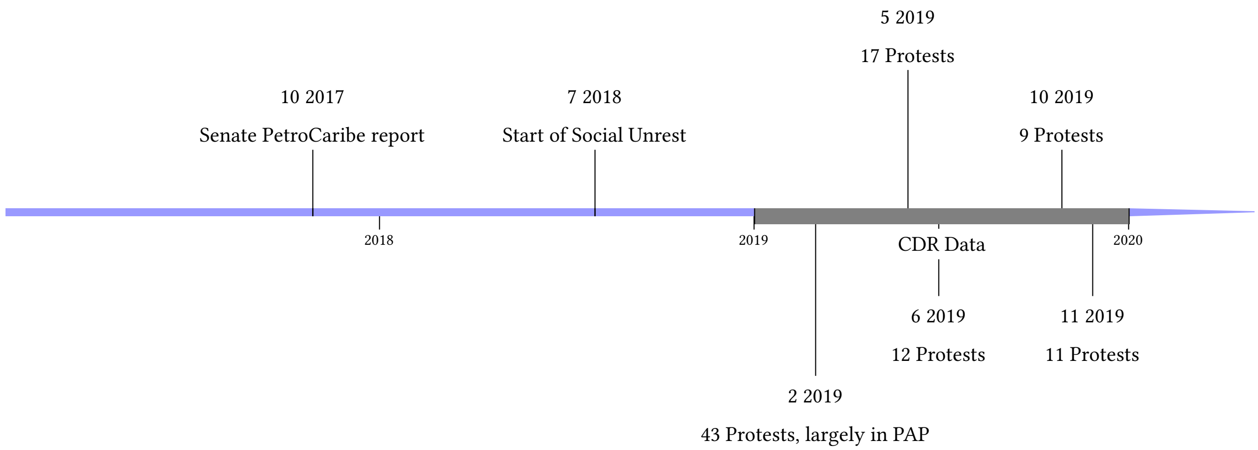

Figure 1: Highlights of Protest Events in Haiti, 2017-2019

tral 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 acute risk of personal harm is involved in the decisions to protest (as it was during this movement). While information might often flow easily through word-of-mouth, when there is a risk associated with passing information on, word-of-mouth 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.[16]

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). 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" (Charles, 2019).

Using this timeline, we zoom in on those events taking place in January-February, 2019. 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).[17] The types of social unrest identified are protests, roadblocks, shootings, rock throwing, and tire burning, which covers the large majority of events throughout the year.[18] 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 US 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 events in Port-Au-Prince in Figure

[16]Other work documents important aspects of diffusion in this context as well: see for example Starbird and Palen (2012) which focuses on meme retweeting during during 2011 Egyptian political uprisings.

[17]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.

[18]The remaining unspecified events are dropped.

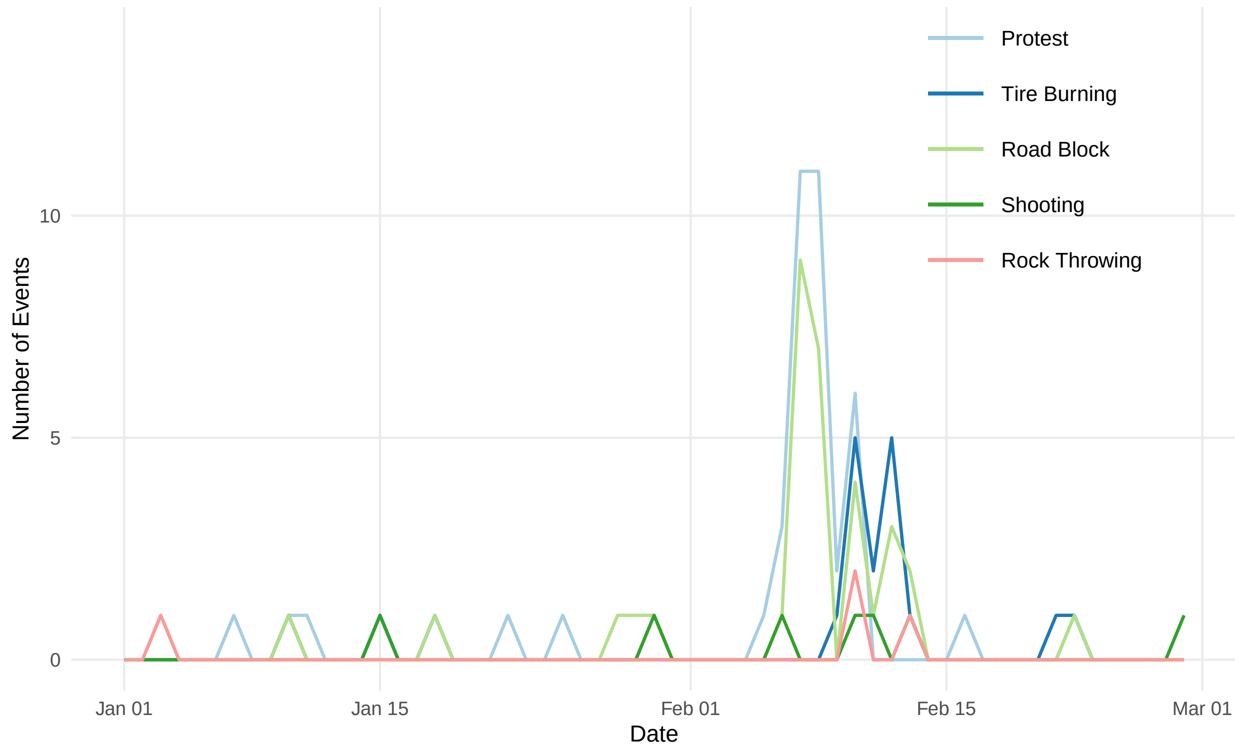

Figure 2: Number of Social Unrest Events by Day in Port-Au-Prince, January and February 2019

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: 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.[19] This is followed by roadblocks, which require just enough people to move a car or some other impediment.[20] Finally, shootings and

[19]"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.

[20]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.

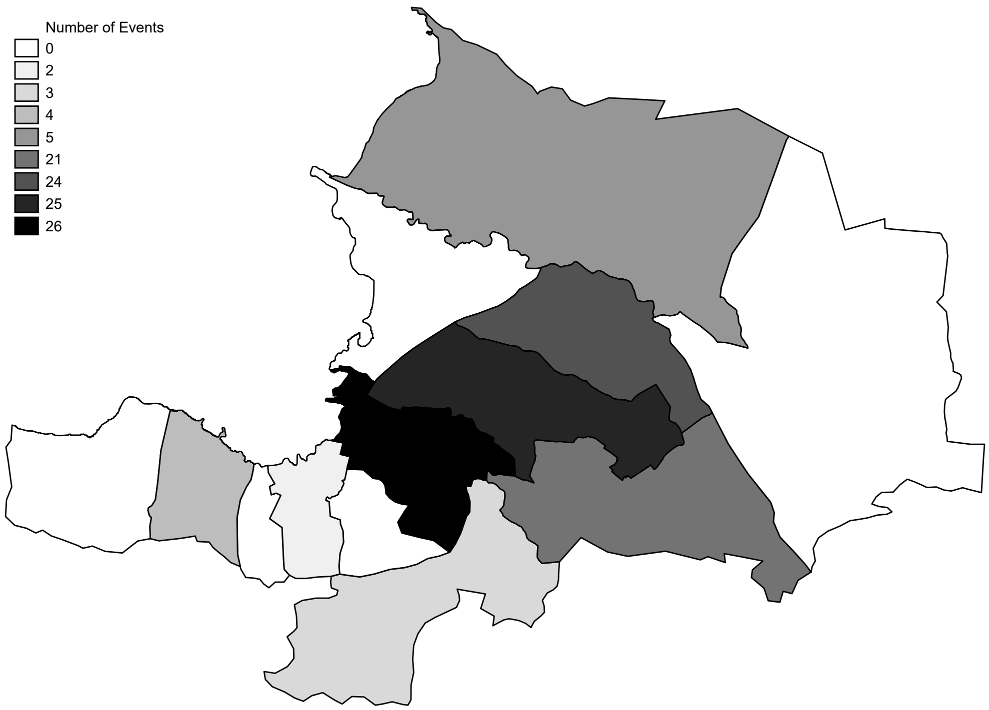

Figure 3: Social Unrest Events in Port-au-Prince, January and February 2019.

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. 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.

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

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

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.

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.[21]

[21]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 Baseline Network: Strong Ties and Centrality

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 and the the number of contacts at baseline to define central nodes, which should be well informed. We define strong ties as those above the 80th percentile in call duration (after omitted dyads with no call duration between them), so about one in five individuals in one's network neighborhood serve as strong ties. We define a high-degree node node as one that has more than 18 contacts at baseline, the average number of contacts in this data. These nodes are above the 67th percentile in the distribution, making up a third of network in this definition. For more on these the process we used to reach these definitions, see Appendix B.1.

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 Social Network Response to Social Unrest

3.1.1 Setup: Utility and Cost Functions

We specify utility for the value of calls with the following functional form, adapting Björkegren (2019):

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

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 ϵ 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.[22]

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.[23]

The utility and cost functions feature eight reasonable properties for cellular call behavior, six

[22]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.

[23]We find this to be a reasonable assumption based on the tradition of work on attention in decision-making. Such a cost might be derived from a capacity model of attention such as the one presented in CITE Attention and Effort.

of which are also important in this application. For more on these properties, please see Appendix A.1.

3.1.2 Optimization: Caller's Problem

The callers problem is as follows:

$$\max_{d_{ijt}\geq 0,\ j\in N(i)} U_i(\mathbf{d}_t) = \sum_{j\in N(i)} \left[\frac{1}{\beta} v_{ij}(d_{ijt}, \epsilon_{ijt}(z_{it})) - (p+\phi(z_{it}))d_{ijt}\right] \tag{3}$$

where $N(i)$ is agent i's neighborhood and β converts units 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.

3.1.3 Solutions: Call Duration

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

$$d^*_{ijt}(\epsilon_{ijt}(z_{it}), \phi(z_{it})) = \left[\epsilon_{ijt}(z_{it})\left(\alpha_{ij} - \beta\left(\phi\left(z_{it}\right) + p\right)\right)\right]^{\frac{1}{\gamma-1}}. \tag{4}$$

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

$$\alpha_{ij} < \beta(\phi(z_{it}) + p) \tag{5}$$

a call will not be made.[24]

[24]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 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 $\phi_{it} = \phi(z_{it})$.

3.2 Comparative Statics

3.2.1 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 5 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.

3.2.2 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.

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

We simplify this expression:

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

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

$$\Delta\epsilon_{ijt}(z_{it})\left(\alpha_{ij} - \beta\left(\phi(z_{it}) + p\right)\right) - \beta\epsilon_{ijt}(z_{it})\phi(z_{it}). \tag{8}$$

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:

$$\left(\frac{\Delta\epsilon_{ijt}(z_{it})}{\Delta\phi(z_{it})}\right)\left(\frac{\alpha_{ij} - \beta\left(\phi(z_{it}) + p\right)}{\beta\ \epsilon_{ijt}(z_{it})}\right) > 1. \tag{9}$$

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

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

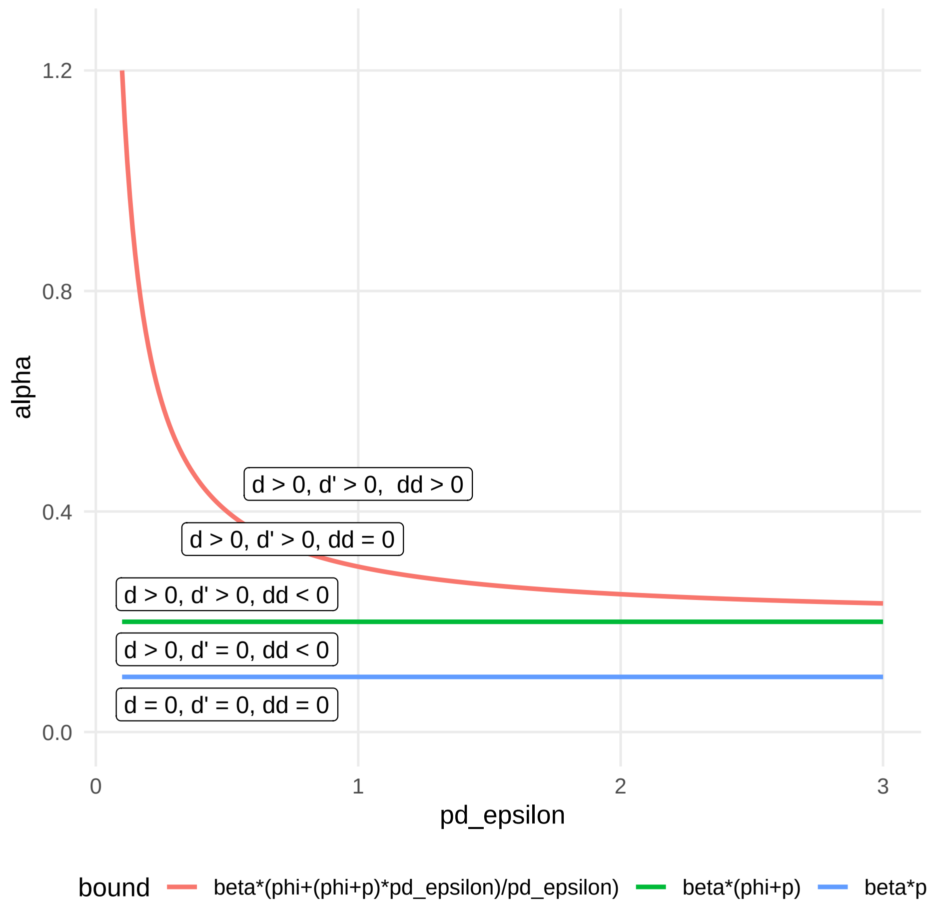

Figure 4: Call response by tie strength and information shock. d is duration with no social unrest, d' is duration with social unrest and dd is the difference in duration. pd_epsilon is the $\%\Delta\epsilon_{ijt}$ and alpha is α_{ij}. Assumes values of $\phi_{it} = p = 0.1$ and $\beta = 1$.

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 10 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.

3.2.3 Aggregation of Dyadic Effects to the Network Neighborhood

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

$$\frac{\partial}{\partial z_{it}} \left\{ \sum_{j \in N(i)} d^*_{ijt}(\epsilon_{ijt}, p) \right\} = \sum_{j \in N(i)} d^*_{ijt} \times \frac{\epsilon'_{ijt}(z_{it}) \left(\alpha_{ij} - \beta \left(\phi(z_{it}) + p\right)\right) - \beta \epsilon_{ijt}(z_{it})(\phi'(z_{it}))}{(\gamma - 1)[\epsilon_{ijt}(z_{it})(\alpha_{ij} - \beta(\phi(z_{it}) + p))]} \tag{11}$$

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 5 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 8 holds.[25] 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.

[25] 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.

3.3 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 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 transmit 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.

3.3.1 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 (ultimately) in previous cases. Thus, we posit that ϵ_{ijt} depends specifically on expectations of neighbors ability to aggregate information. The process by which individuals would identify potentially informed sources 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 receiver's perspective. However, since we have shown that very weak ties will not be called, the ego will not call out of its network neighborhood. In this case, Banerjee et al. (2019) shows that diffusion centrality will be proportional to (out)degree centrality. Therefore, $E(\epsilon_{ijt})$ should be directly proportional to alter degree – meaning individuals call their high degree neighbors in a crisis.

3.3.2 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). This idea suggests that while those you communicate with frequently have information which overlaps with your own, those weaker ties may have novel information. In our model, this might be embodied by a inverse relationship between in the strength of tie and the size of ϵ_{ijt}.[26]

3.4 Hypotheses

From this model, stylized facts about social networks, and the acuteness of the social unrest shock in this context, we arrive at four 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.*

(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

[26] 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.

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.

We posit that the size of the information shock may be related to the degree centrality. Furthermore, weak ties may have larger information flow between them.

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.

We start with traditional difference-in-difference approaches to build intution. The estimating equation for difference-in-differences without individual fixed effects is written

$$y_{ilt} = \alpha + \beta \,\text{Unrest}_{il} + \gamma \,\text{Post}_t + \delta \,\text{Unrest}_{il} \times \text{Post}_t + \epsilon_{ilt} \tag{12}$$

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, this specification may be a poor fit for this context. This approach 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

$$y_{ilt} = \alpha + \beta \text{ Unrest}_{il} + \gamma \text{ Episode}_{lt} + \delta \text{ Unrest}_{il} \times \text{Episode}_{lt} + \epsilon_{ilt} \tag{13}$$

where Episode_{lt} is an indicator variable (equal to 1 when unrest is taking place). We will refer to this as the DiD specification. Finally, we might estimate this specification with two-way fixed effects, which we will refer to as the TWFE specification:

$$y_{ilt} = \beta_i + \gamma_t + \delta \text{ Unrest}_{il} \times \text{Episode}_{lt} + \epsilon_{ilt}. \tag{14}$$

However, a non-absorbing treatment is not the only wrinkle we face in estimating our parameter of interest. Our context features variation in timing of social unrest, which has implications for the estimation of treatment effects when they are heterogeneous across units or time (Goodman-Bacon, 2019; de Chaisemartin and D'Haultfœuille, 2020). The treatment effect estimated using this TWFE specification will be a weighted average of treatment effects computed from the various treatment and comparison groups. In the context of our event-only DiD, and TWFE estimator, this would create comparison groups where people faced with unrest at a later date would be compared to those who face *ongoing* unrest.[27] Using a treatment group for comparison for a newly treated group will produce an underestimate of the treatment effect for that comparison. Moreover, the weights themselves are often unreasonable and an artifact of the estimation procedure. 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

[27] An instructive example is presented in Goodman-Bacon (2019): 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 act as controls even after they have received treatment.

(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. The authors provide two tests that can be used to diagnose the potential for these issues (which we will describe in Section 5.1.1) 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. Some of these conditions involve restrictions on the data structure and can be quickly (and directly) verified. Others must be maintained.

There are three assumptions which we can quickly verify. 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. 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. 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.

However, to estimate DID^M we must maintain another five assumptions that 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.[28] 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.[29]

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.[30] We document these pre-treatment trends in section 5.3.2. Likewise, for those who leave treatment we invert this common trends assumption to consider common trends among treated areas.[31] 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.[32]

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

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

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

[30]That is, for $t \geq 2$, $E(Y_{l,t}(0) - Y_{l,t-1}(0))$ does not vary across groups 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.

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

[32]Formally, for all l,t, $E(Y_{l,t}(0)|\mathbf{D}) = E(Y_{l,t}(0)|\mathbf{D}_g)$ and $E(Y_{l,t}(1)|\mathbf{D}) = E(Y_{l,t}(1)|\mathbf{D}_g)$. While we cannot test this assumption, we are able to document by analyzing the sensitivity of treatment effects to the distance at which a tower becomes treated, and hope to do so in the future.

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 Data Processing, Estimation, and Standard Errors

After cleaning, we process transactions from voice calls made in Haiti in January and 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). 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 and social unrest events 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 Port-Au-Prince region.[33] 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

[33]To do this, we select sub-commune boundaries, also 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. The selected communal sections can be seen in figure 3, for example.

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 three week baseline period, 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.[34]

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 Port-Au-Prince.

[34]Notably, past work with call detail records in Por-Au-Prince suggest mobility is low. In particular, Zagatti et al. (2018) find that only 42% of people in the Por-Au-Prince area travel more than 1km to work.

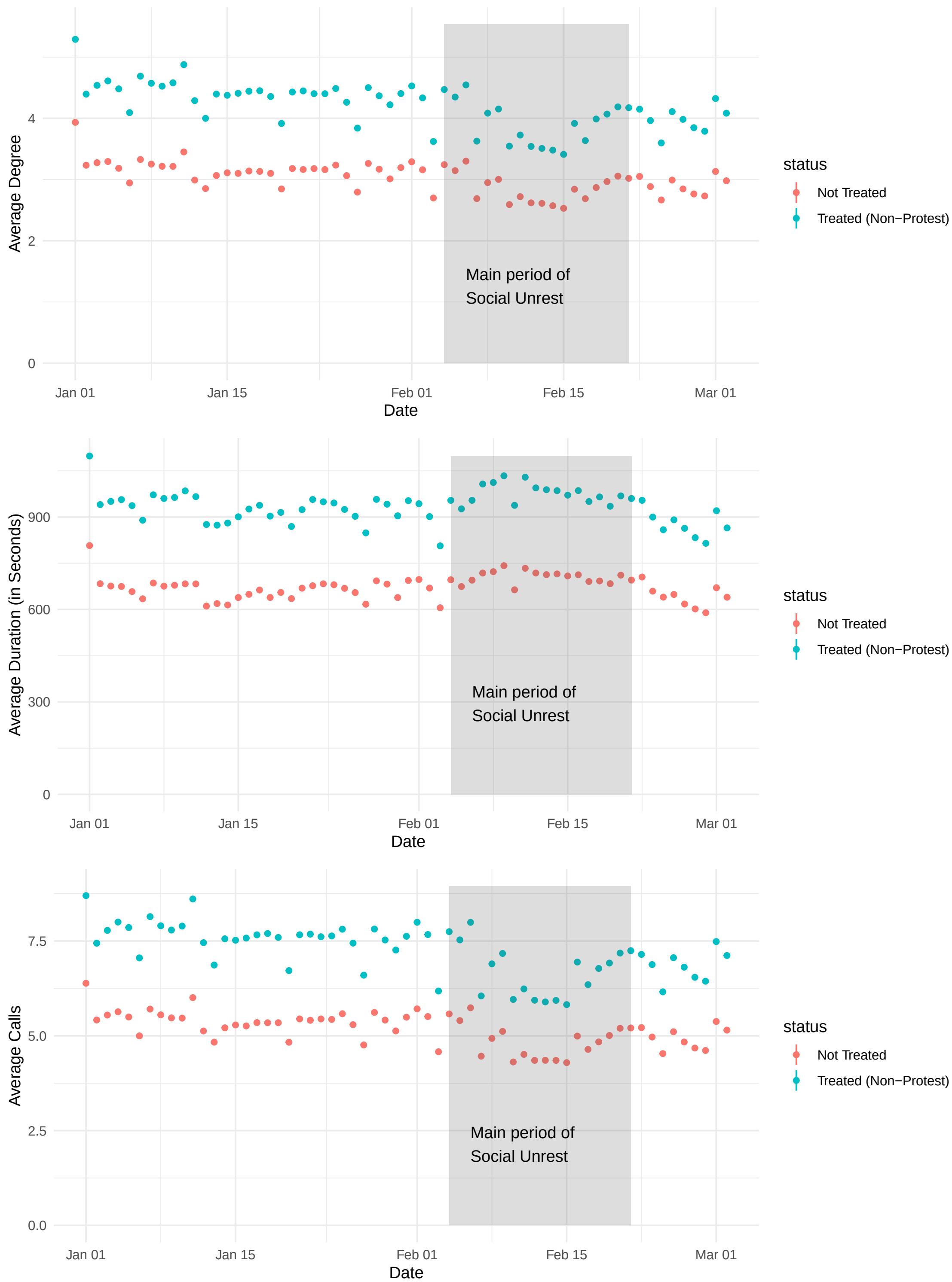

Figure 5: Average degree, duration, and calls over the sample period by exposure to non-protest social unrest event.

4.3.4 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 location are considered 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 Main Effects: Non-Protest Social Unrest Events

5.1.1 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

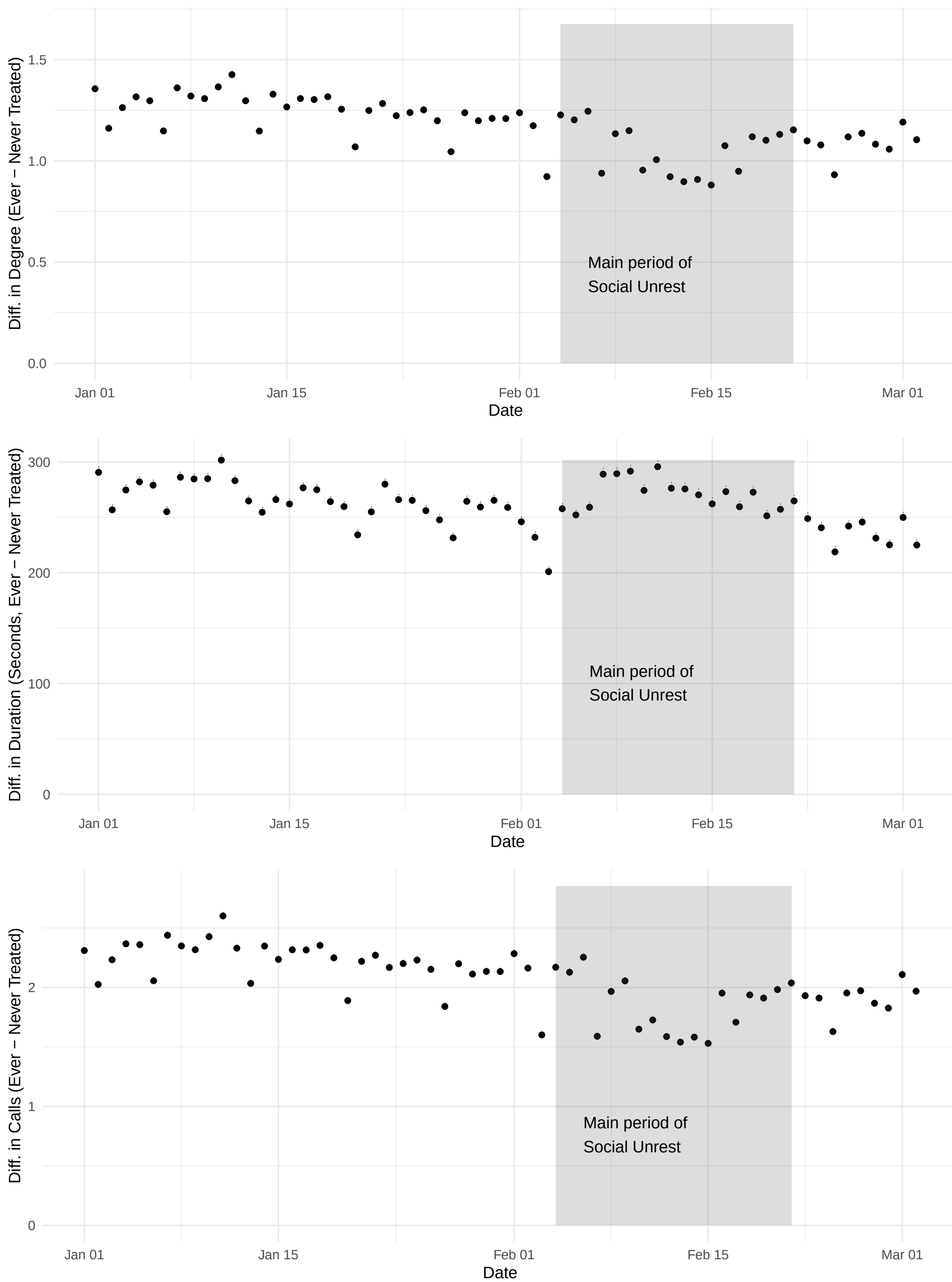

Figure 6: Differences in degree, duration, and calls over the sample period by exposure to non-protest social unrest event.

Table 3: Effects of Social Unrest on Network Degree

	Degree (Total Contacts)		
	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

equal to 0, meaning changes in weights could lead to reversals in the sign of the treatment effect. 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.

5.1.2 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.

Despite the concordance in sign between the DID^M estimates and the TWFE estimates on contacts and calls within this sample, our estimates differ in magnitude across these estimation methods. While coefficients are on the same order of magnitude, the differences in results do matter in a quantitative sense. 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. We interpret these differences in coefficient as reflecting differences in weighting between the TWFE and DID^M estimators. Given the known problem with TWFE weights when treatment effects are heterogeneous and there is variation in treatment timing, 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.[35]

5.1.3 Estimates and Interpretation of Causal Effects

Using DID^M we estimate episodes of social unrest reduce degree by 0.048 contacts, but does not spend significantly less time talking on the phone. Considered another way, individuals spend *more* time talking per 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.

[35]When errors are homoskedastic and uncorrelated, TWFE may yield a lower variance estimate than DID^M 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.

Table 4: Effects of Social Unrest on Total Call Duration

	Total Duration (in seconds)		
	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	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

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.[36] 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.

[36]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: Decomposing DID^M Estimates of Social Unrest on Degree

	DID^M Estimates		Pre-Unrest‡		
Restrictions	Effect	Std Err.†	Mean	Std Dev.	Scaled Effect§
(None: Main Effect)	-0.0478	0.0145	3.107	4.418	-0.015
Strong Ties (Any Info)	-0.0340	0.0090	1.274	2.224	-0.027
Informed Ties (Any Strength)	-0.0201	0.0067	1.833	2.819	-0.011
Strong & Informed Ties	-0.0221	0.0060	0.798	2.145	-0.028
Strong & Uninformed Ties	0.0020	0.0030	0.475	1.052	0.004
Weak & Informed Ties	-0.0118	0.0050	0.563	1.602	-0.021
Weak & Uninformed Ties	-0.0158	0.0091	1.270	1.951	-0.012

Notes:

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
† Block bootstrap with 500 repetitions
‡First ten days of data, pre-main period of social unrest
§ Scaled Effect = Effect / Pre-Unrest Mean

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.

5.2 Decomposing Results by Tie Strength and Information

While these results paint a picture consistent with our theoretical model, more extensive testing of the model hypotheses is needed. In this section, we provide evidence around strong and weak ties as well as high and low information ties. We decompose the results by restricting what relationships are included when we construct outcomes. For example, strong and informed tie degree would computed by adding only the contacts who were both strong ties and had high-degree at baseline.[37] If we find more positive (or less negative) coefficients on social unrest on these restricted outcomes, this would provide evidence that people people value these connections in uncertain situations. These estimates decompose the treatment effect into peer subgroups. By construction, the sum of the subgroup effects equal the effect of all subgroups. For example, the sum of effects on strong ties and weak ties will equal the main (unrestricted) effect.

Table 5 presents results for degree (total contacts). While total contacts fall, this is not evenly distributed across subgroups. In particular, for those connections who are strong and uninformed ties, we actually find that contacts do not fall. This suggests that people want information about their close friends, family, or associates. We also find a smaller reduction compared to baseline for people's weak uninformed ties, an effect that may require greater exploration. Finally, informed ties (both strong and weak) have a relatively large reduction in terms of contacts. This may provide evidence against "strength of weak ties" in this case (Granovetter, 1973). Table 6 presents the decomposition of effects on duration of calls. As is the case with the main effect, the subgroup effects are null results. This pattern of results reflects search for a very limited form of information. Instead of learning about the state of the world generally, individuals seek information about realities for those people that are close to them and recede from searching for other information.

5.3 Addressing Threats to Validity

5.3.1 Network Measurement

A first potential threat to validity 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 though nodes 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.

[37]To recall, strong ties are those alters with dyadic duration above 80th percentile in three week baseline period. Informed alters are those have degree above 67th percentile in the baseline period.

Table 6: Decomposing DID^M Estimates of Social Unrest on Total Call Duration

	DID^M Estimates		Pre-Unrest‡		
Restrictions	Effect	Std Err.†	Mean	Std Dev.	Scaled Effect§
(None: Main Effect)	-4.45	5.86	663.6	1484.1	-0.007
Strong Ties (Any Info)	0.96	5.08	436.2	1266.6	0.002
Informed Ties (Any Strength)	0.56	3.91	297.4	1063.3	0.002
Strong & Informed Ties	2.07	3.53	241.6	978.2	0.009
Strong & Uninformed Ties	-1.11	3.13	194.6	861.1	-0.006
Weak & Informed Ties	-1.51	1.39	55.7	228.5	-0.027
Weak & Uninformed Ties	-3.90	3.55	171.6	515.2	-0.023

Notes:
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.
† Block bootstrap with 500 repetitions
‡First ten days of data, pre-main period of social unrest
§ Scaled Effect = Effect / Pre-Unrest Mean

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, 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 in-person social networks. 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 (i.e., have opposite sign) from the proxy at hand.

5.3.2 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 5 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.

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, 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.

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. Decomposing these results, we find evidence the people check in on these close ties but do not reach out to individuals who, due to their centrality at baseline, might be more informed about the crisis at hand.

6.2 Further Tests of Robustness

Just as more evidence around what types of connections are valued is needed, assessing other threats to the validity of our estimates is a pressing concern going forward. 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 Toward Network Change

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). However, the evolution of networks has long been of interest to economists and other computational social scientists remains an important goal of our broader project.[38]

Much of the work studying long term network change within the development literature emphasizes the introduction of programs, products or the expansion of markets. 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). Finally, Gagnon and Goyal (2017) present a theoretical framework to understand how market participation and network participation might complement and substitute for each other.

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

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

while the latter will allow us to investigate how specific dyads embedded within the network change over time.

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A Theoretical Appendix

A.1 Useful Properties of the Utility Function

We build on the theoretical model from Björkegren (2019). In particular, that paper uses the utility function

$$v(d, \varepsilon) = d - \frac{1}{\epsilon}\left[\frac{d^\gamma}{\gamma} + \alpha\right]. \tag{15}$$

Our adaption of this utility function features six useful properties:[39]

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, $\frac{\partial^2 d^*}{\partial c \partial \epsilon} < 0$

[39]The two others in Björkegren (2019) are as follows. 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.

A.2 Diffusion Centrality and High Information Nodes

A.2.1 Hearing Matrix

The hearing matrix presented in Banerjee et al. (2019) is defined as

$$\mathbf{H}(\mathbf{D}, S) = \sum_{s=1}^{S} \mathbf{D}^{s} \tag{16}$$

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

$$NG(\mathbf{D}, S)_j = H(\mathbf{D}, S)_j. \tag{17}$$

However, at single remove from the node (i.e., $S = 1$) the authors show that diffusion centrality is proportional to (out-degree centrality) (Banerjee et al., 2019). Therefore, if we assume the caller cannot call out of their network neighborhood, then they will aim to call those with the highest centrality in their neighborhood.

A.2.2 Refinements to Diffusion Centrality

King (2020) makes the argument that diffusion centrality double counts information flows presents three additional concepts that refine diffusion centrality: *word-of-mouth*, *obstructed*, and *visibility centrality*. The author 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.[40] 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. 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

[40] 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.

$j \in N(i)$ to be more efficient, building a sparse matrix of centralities.

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.

B Empirical Appendix

B.1 Variables for Heterogeneity Analysis

B.1.1 Defining Strong Ties in the Data

Since the histogram of the total duration of calls (figure 7) 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 7 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.[41]

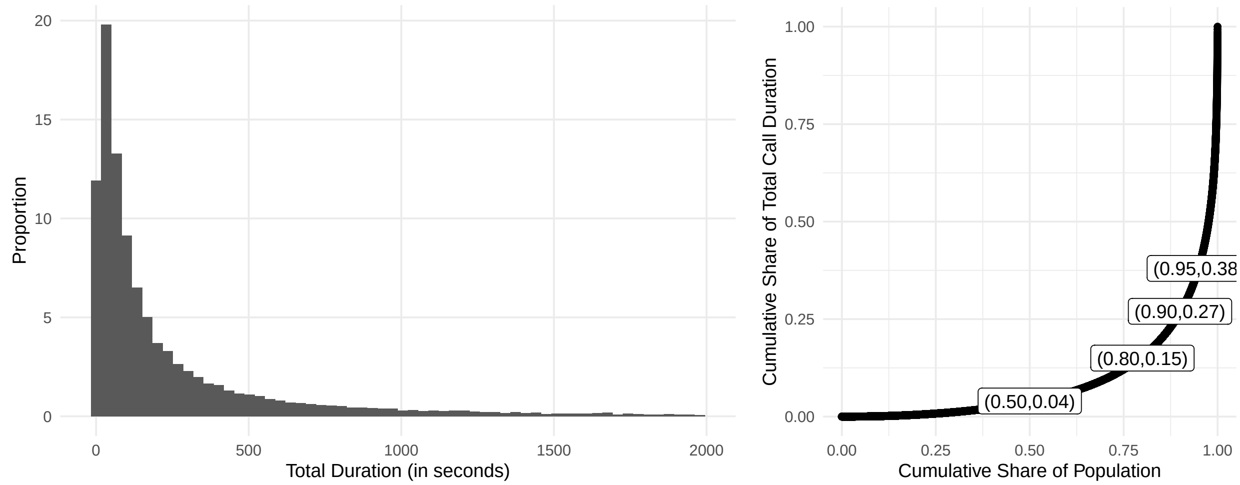

Figure 7: Histogram (left) and Lorenz curve (right) of total call duration over dyads in baseline network

B.1.2 Locating Likely Informed Nodes

We hypothesize that nodes with high degree at baseline are likely to be well informed when social unrest takes place. To proxy for likely informed nodes, we plot the degree (as well as other network statistics) of these nodes in the baseline in figure 8. 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.

[41]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:

$$\text{Jaccard}(i, j) = \frac{\text{Total number of overlapping connections between } i \text{ and } j}{\text{Total number neighbors of } i \text{ of } j} \tag{18}$$

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.

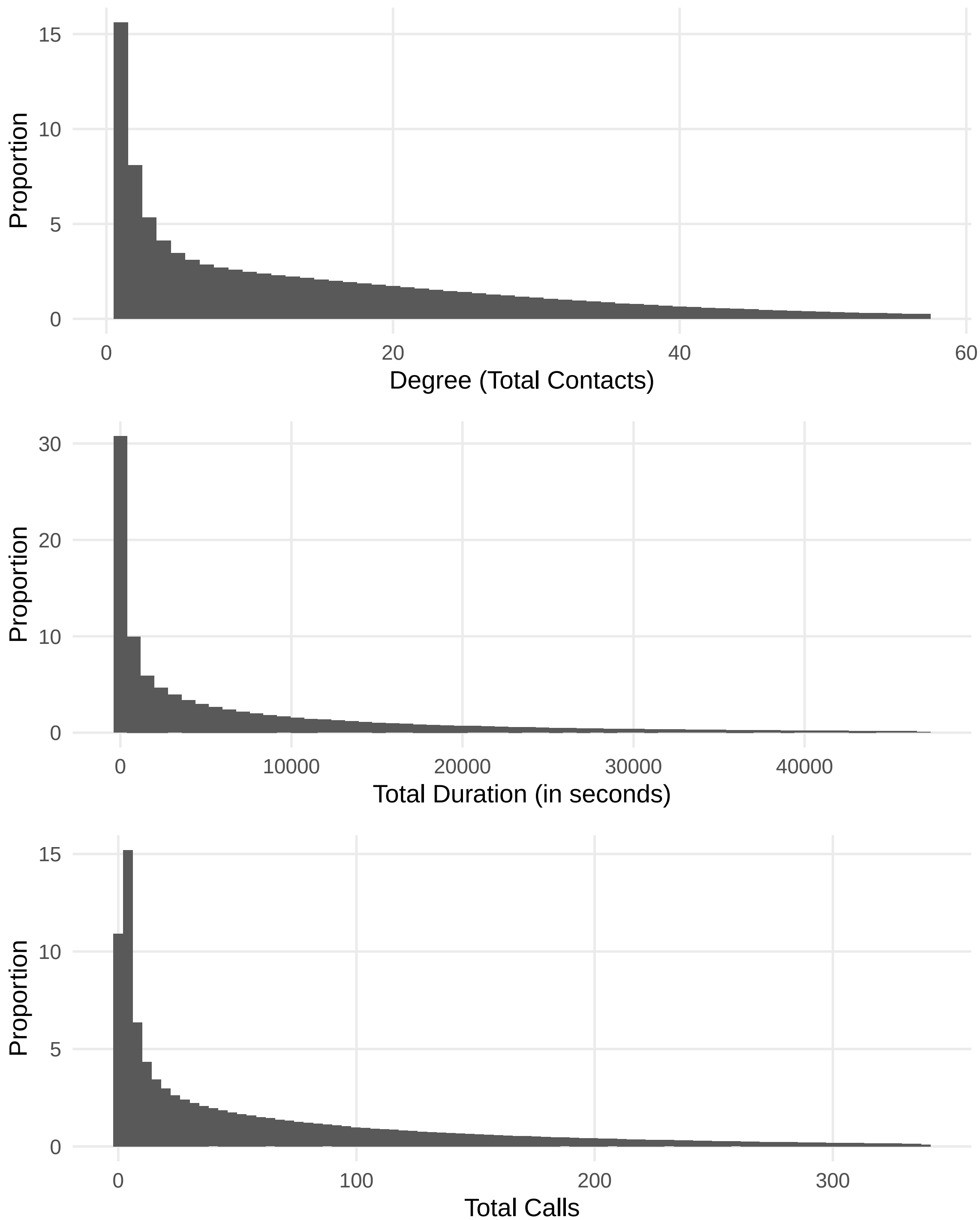

Figure 8: Histogram of node level outcomes in baseline network

B.2 Effects on Total Calls

Effects on total calls are presented in . Using DID^M we estimate episodes of social unrest reduce calls by 0.103.

C Additional Figures

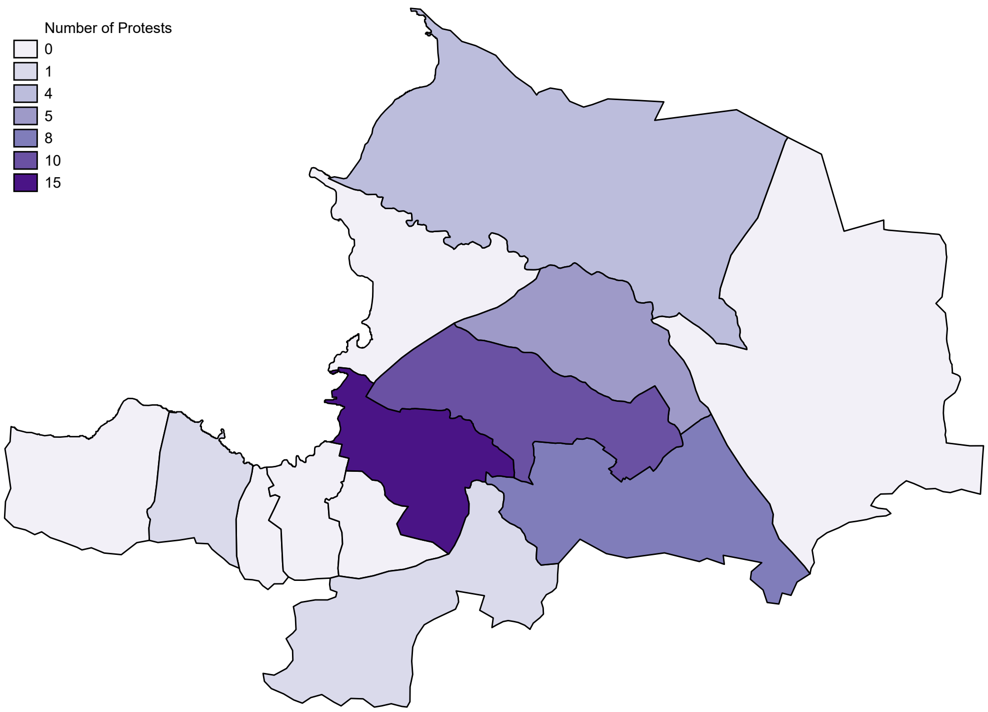

Figure 9: Protests in Port-au-Prince, January and February 2019.

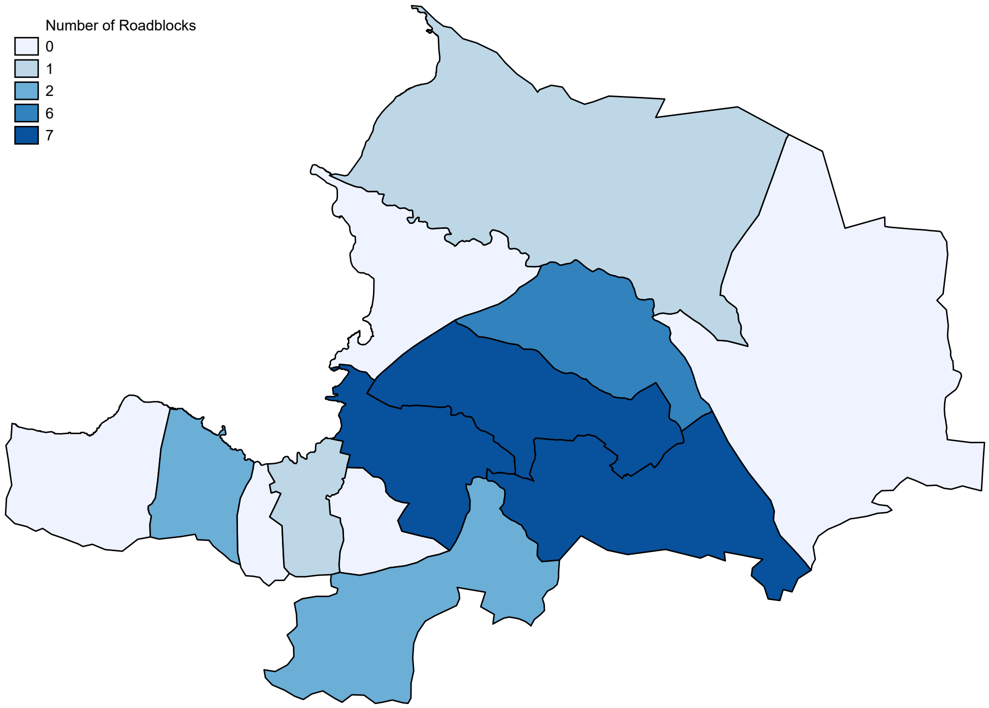

Figure 10: Roadblocks in Port-au-Prince, January and February 2019.

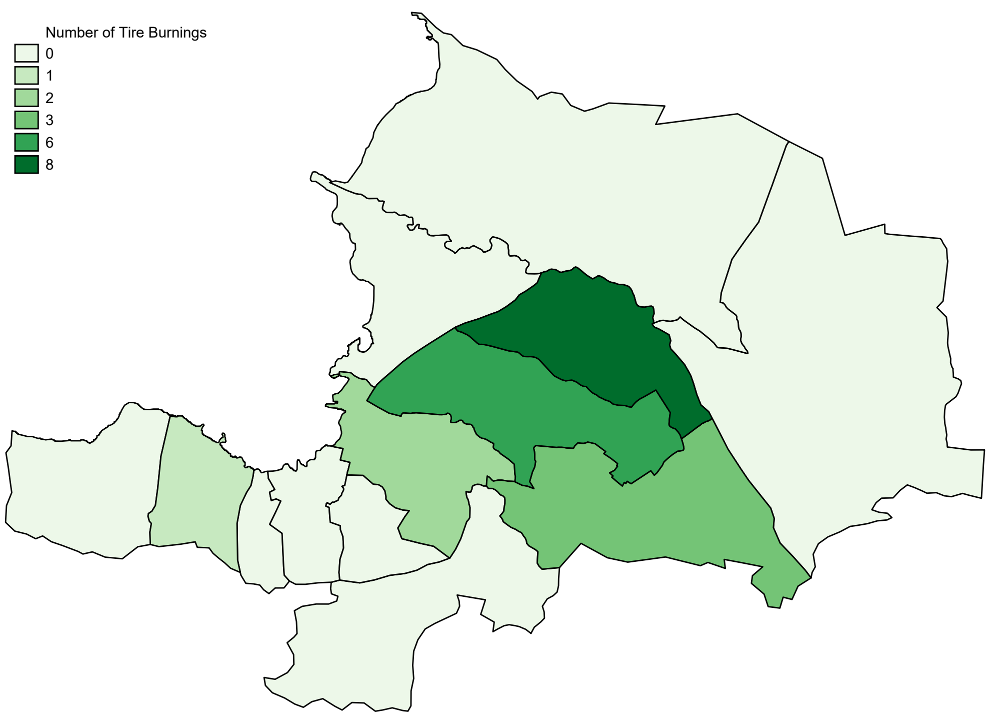

Figure 11: Tire Burning Events in Port-au-Prince, January and February 2019.

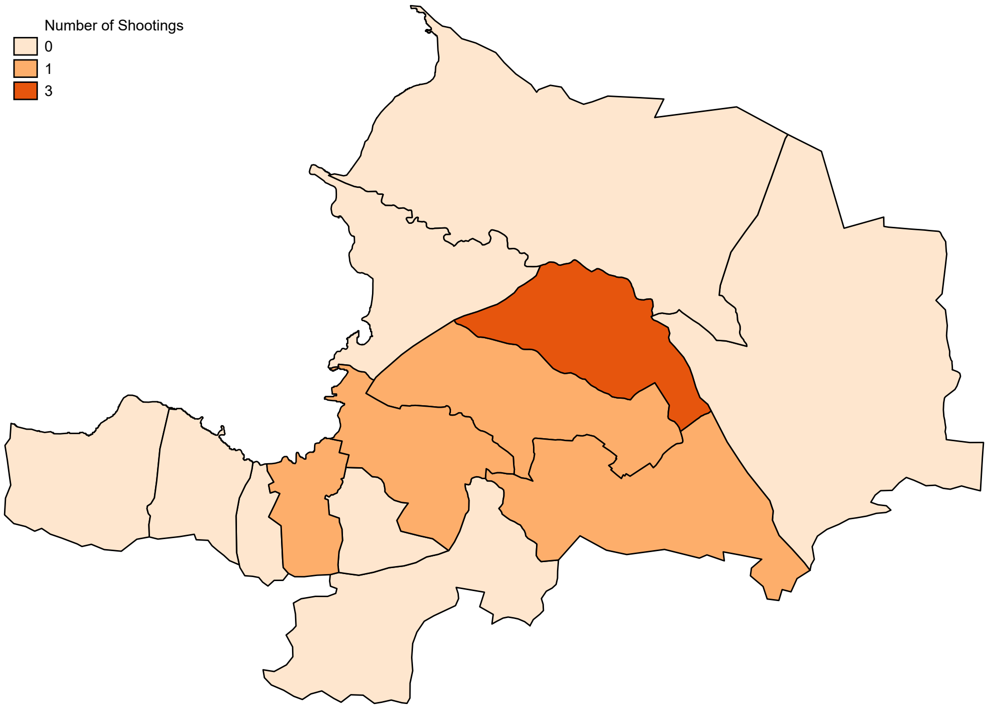

Figure 12: Shootings in Port-au-Prince, January and February 2019.

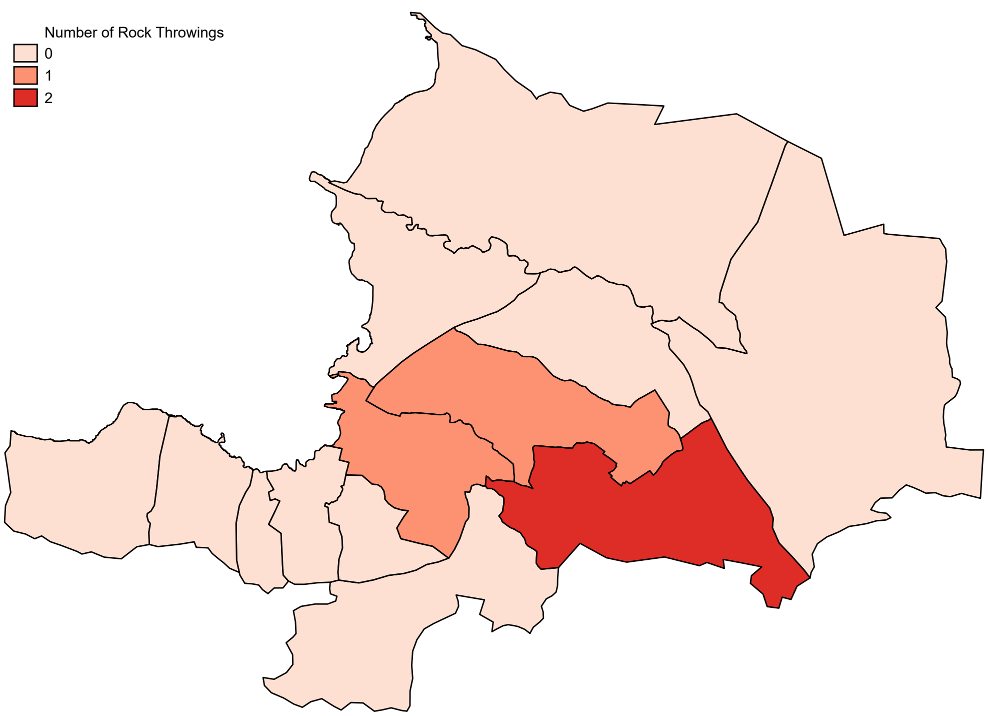

Figure 13: Rock Throwing Events in Port-au-Prince, January and February 2019.

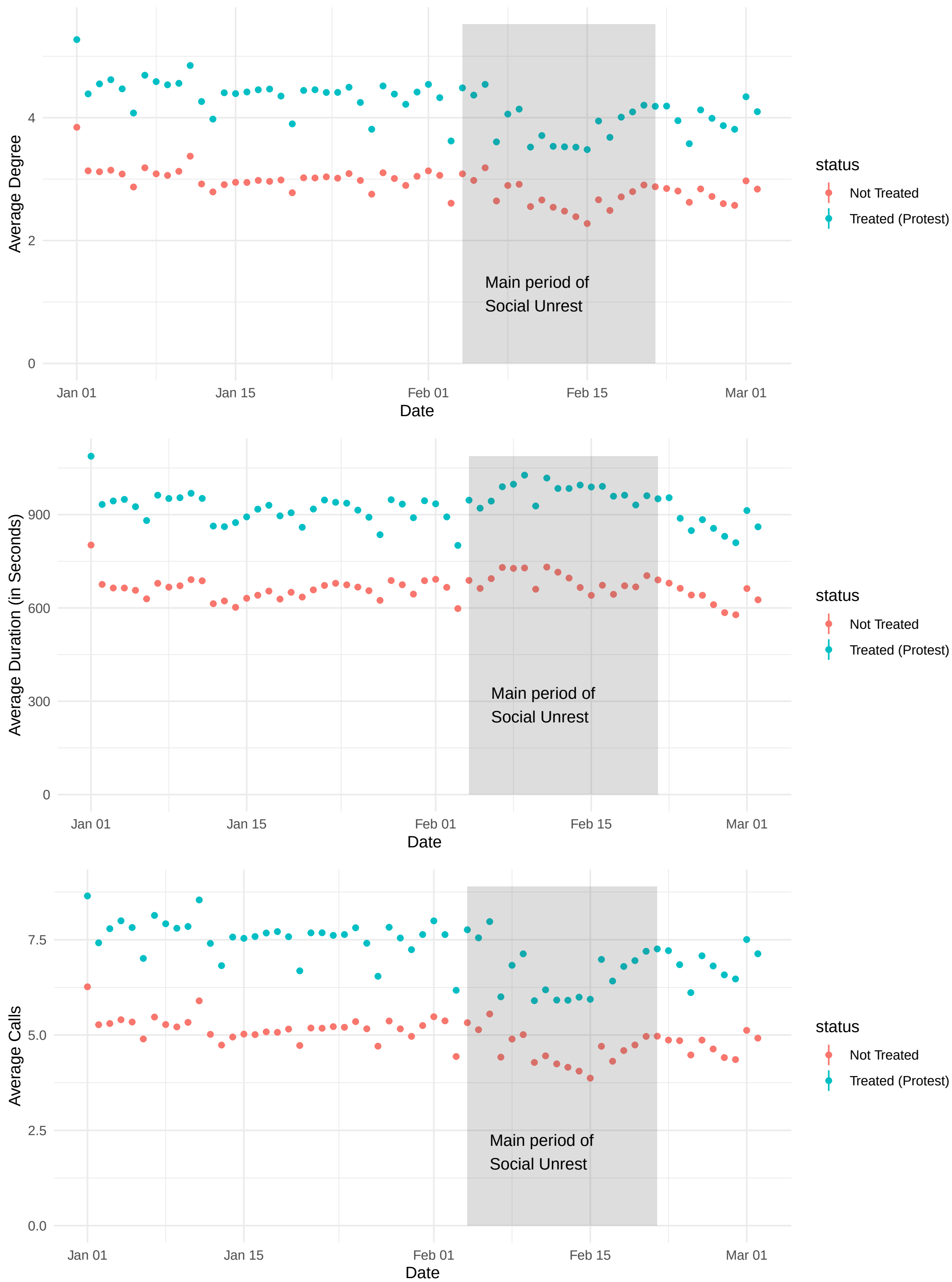

Figure 14: Average degree, duration, and calls over the sample period by exposure to protest.

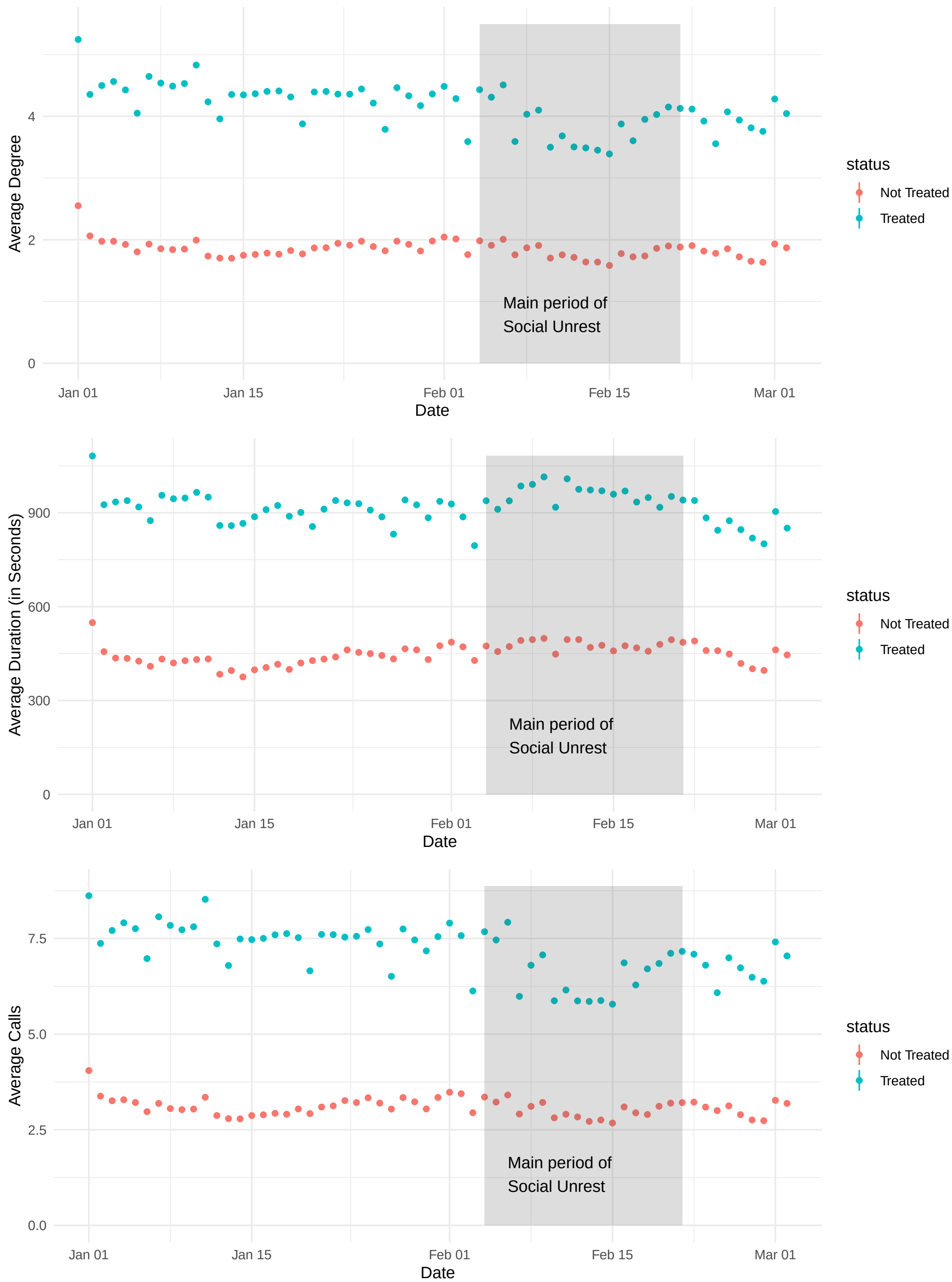

Figure 15: Average degree, duration, and calls over the sample period by exposure to any form of social unrest.

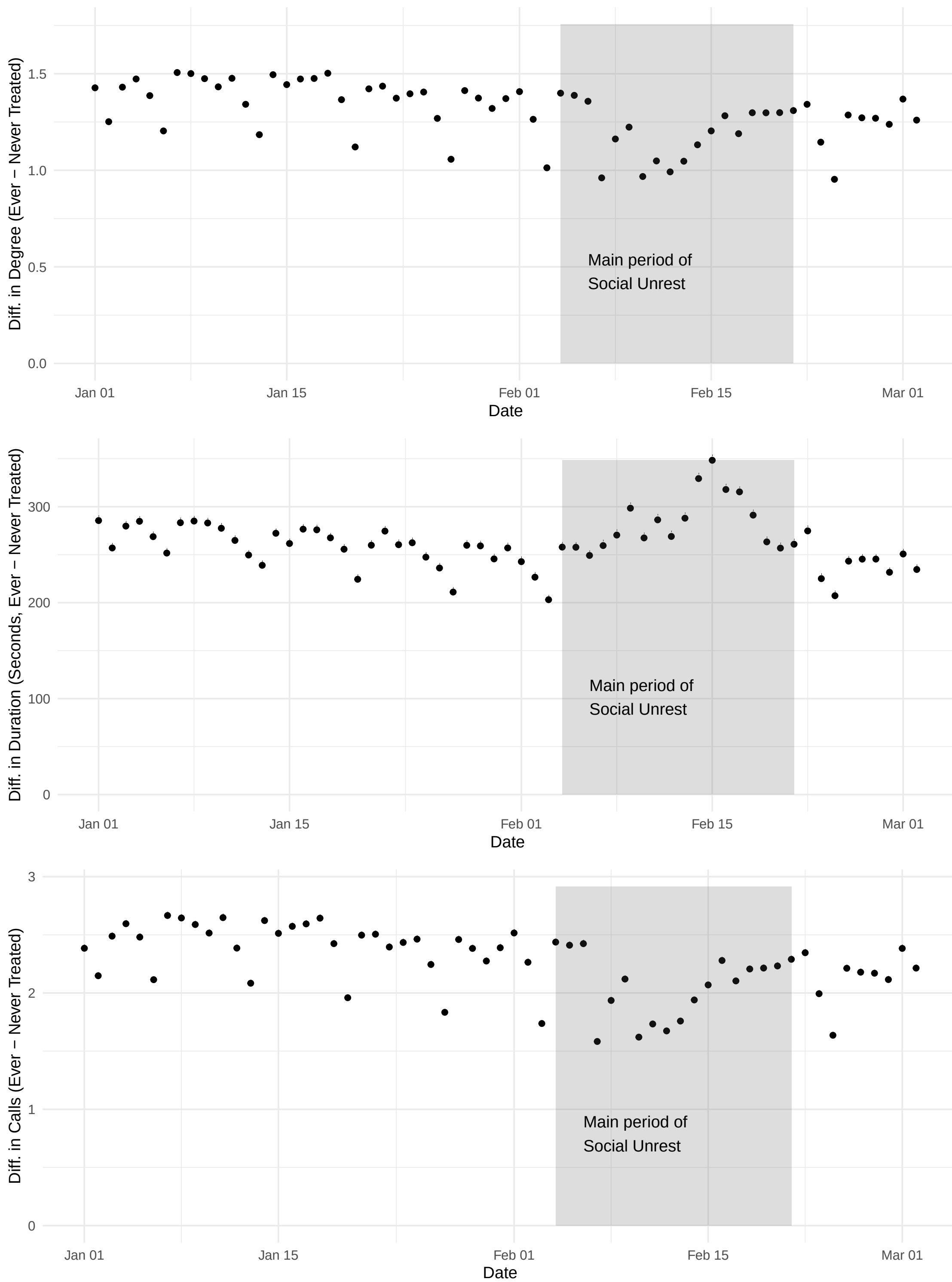

Figure 16: Difference in degree, duration, and calls over the sample period by exposure to protest.

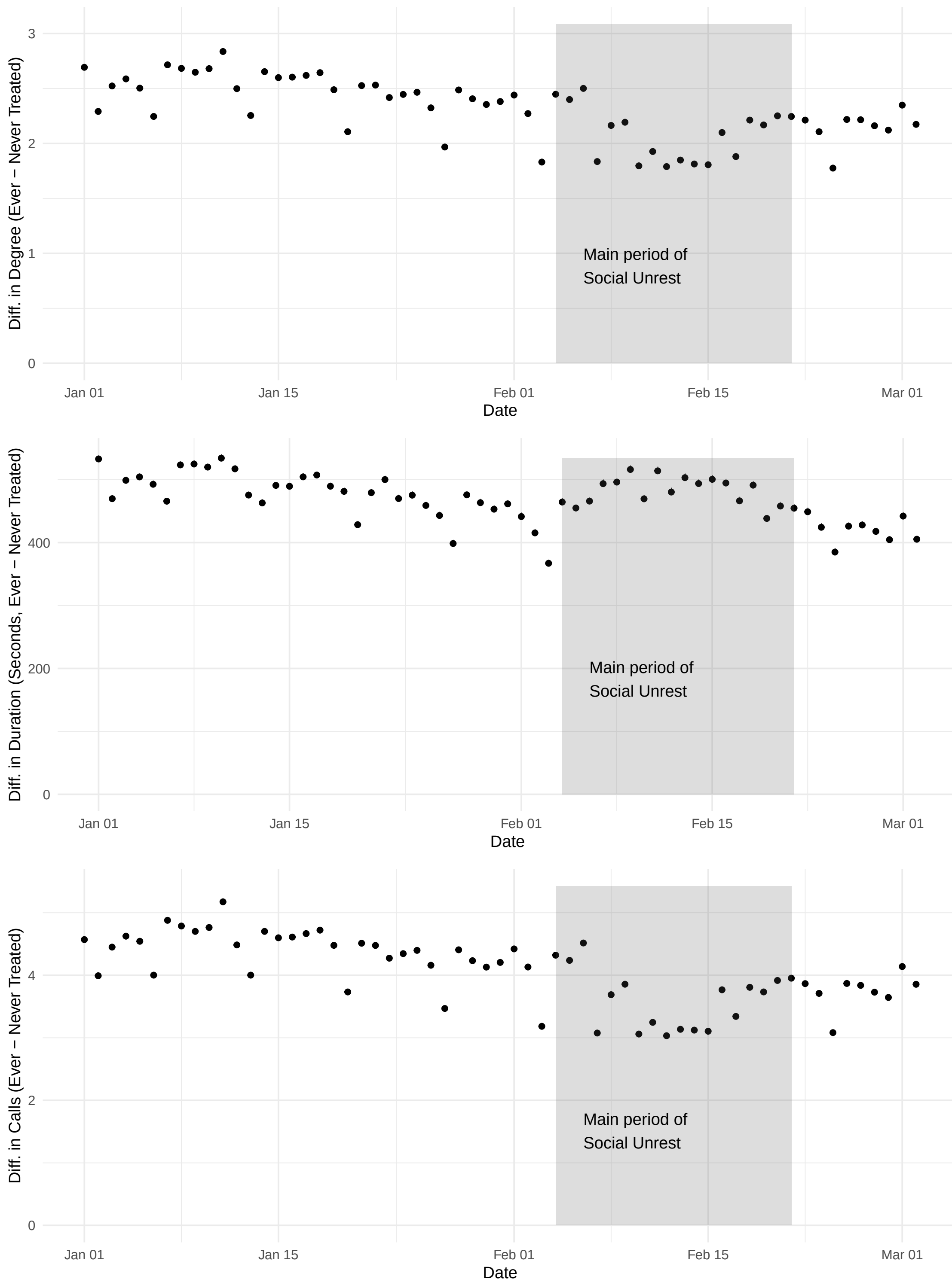

Figure 17: Difference in degree, duration, and calls over the sample period by exposure to any form of social unrest.