You will hear of skirmishes and rumors of skirmishes: Cell Communication in Proximity to Political Violence

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Abstract

We investigate the relationship between low-level political violence and communication patterns. Using network traffic from all Orange Côte d'Ivoire cell towers and 400 million calls from 500,000 randomly sampled cell phone subscribers, we show that in the days preceding small violent incidents, call volumes increase, driven by more active subscribers. Average call length decreases and calls become more local. This suggests that the tension preceding political violence is widely dispersed among members of the local population. These changes are consistent with people calling close friends and family at a higher rate. These unique communication patterns attenuate as we increase distance from the violence and strengthens as we exclude nonfatal events. We further show that the signature for violence is significantly different than those of football matches and festivals.

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1 Introduction

While politics in developed countries is figuratively referred to as a blood sport, in developing democracies this can be literally true. Armed youth wings of political parties attack each other. Voters are intimidated away from going to the polls. Even months after elections, opposition supporters can be the targets of attacks. Though far more common and less remarked upon than headline-grabbing battles, these politically-motivated skirmishes inflame group attachment (Wilkinson (2004)), prolong and spread instability, and impact long term economic growth (Sambanis (2004), Lujala *et al.* (2005)). However, little is known about low level violence; observers have a tendency to regard them as random, and hence impossible to anticipate, but careful qualitative studies suggested that this perception is due to lack of information (Senaratne (1997) Kalyvas (2003)). We pierce this fog to reveal that local communication patterns change a few days ahead in a way that indeed suggests anticipation of a troubling event, supporting theories that such violence is not random.

Changes in behavior in the days surrounding low-level violence sheds light on the nature of these skirmishes. However, social science has historically had a hard time examining this window of time exactly because such violence often happens too unexpectedly (from the researchers perspective) to plan data collection. This void in the quantitative social science literature cannot be completely filled by qualitative interviews performed afterwards, as authors such as Schacter & Coyle (1997) show that memories in relation to stressful events are particularly biased. However, the widespread availability of mobile phones provides a continuous, real time stream of data at a high level of spatial precision. We take advantage of this to probe behavior at a previously unattainable level of temporal and spatial proximity to ordinary low-level political violence.

We use anonymized call records in Côte dIvoire provided to us by Orange Telecom to show for the first time in the literature on political violence how ordinary people behaves in the days immediately surrounding common, low-level political violence.[1] The existing literature provides the framework on which we build our hypotheses. Bagrow *et al.* (2011) show that when unexpected events occur (e.g plane crashes, terrorist bombings), we can detect a sharp jump in cell phone usage which then decays; this is known as the jump decay pattern. Apart from call volume, changes in call destinations may also reveal shifts in the motivation behind communication. While (Pierskalla & Hollenbach (2013) find that mobile activity in rebel organizing is directed towards geographically distant locations, Cohen & Lemish (2005) and Blumenstock *et al.* (2014) observe

[1] The call records span the period from December 2011 to April 2012, which is seven months after the end of the Second Ivorian Civil War, a period where low-level violent flare ups are a problem across the country. We combine this with peacekeeping records from the United Nations Operations in Côte dIvoire (UNOCI).

that mobile activity after terrorist attacks and natural disasters are directed towards closer reciprocal and geographical links, which may relate to a large literature in social psychology on the effect of crises on the need for social support (Thoits (2011), Shea *et al.* (2015)).

Focusing our investigation on call volumes on the days immediately before and after skirmishes, we see no evidence for the jump-decay pattern. Instead, local call volumes increase by on average 10% in the days leading up to the event, accompanied by a 6% increase in the number of active cell phone. The change of behavior before the event implies that low-level political violence is not analogous to terrorist bombings which are designed to be and usually successful at being an absolute surprise to locals (Bracken *et al.* (2005)). Rather, a vast number of people are changing their behavior, suggesting that they are either directly aware that violence is likely or indirectly aware, simply knowing that something is different. The results of this paper is consistent with the observations of Senaratne (1997) and Kalyvas (2003) that seemingly indiscriminate low-level violence may have actually been predictable given local information .

Although specific call destinations are not available for our data due to privacy reasons, we can probe into the changing nature of the calls in a novel way. Friends and families often share the same network to minimize out of network calling fees;[2] and hence a preference for closer reciprocal links will be reflected by a shift towards same network calls. Indeed we see a dramatic (16%) increase of same network calls starting a few days before the event, peaking at the day of the skirmish, before slowly returning to normal a few days after the event. These calls are shorter and are more likely to be directed towards a geographically closer antenna than calls in normal times; a pattern that is entirely different than anticipation of non-violent events such as sporting matches or festivals.[3] Overall, the evidence more closely resemble the inward response to unsettling events (Shea *et al.* (2015), Cohen & Lemish (2005), Blumenstock *et al.* (2014))) rather than the outward orientation in positively experienced events (Fredrickson, 2001) or coordination activities (Pierskalla & Hollenbach (2013)). This tendency to turn towards close relational and geographical ties in anticipation of a crisis may spread rumors about violence, thus serving as the micro-level mechanism linking political violence to stronger group attachment (Wilkinson (2004)).

The usual approach in studying political violence focuses on events with at least 25 deaths (Themnér & Wallensteen (2011)) and use fatalities and mass displacement as the measure of the intensity of violence (Kasara (2011)). Given these standards, the low level violence in this paper

[2]Preferential fare for within-network calls as "...a welcoming offer to invite friends to use the ...network" is a common competitive practice to widen a telecom companys subscriber base (`http://www.wap.ratio-magazine.com/inner.php?id=220`). See also: `http://www.ainewswire.com/?p=336`.

[3]For example, the local mood in the days surrounding the division 1 soccer matches (Côte dIvoire Ligue 1) appears outwardly oriented: antennas near the location of the match record more out-of-network calls, call of longer durations, and communication with geographically further antennas.

could be easily overlooked due to their low fatality count and negligible population displacement.[4] However, this paper shows that studying these small events not only reveal their non-randomness, but also illustrates that it may not take much to activate the micro-level mechanism that can spread unease and insecurity. As for extrapolating to communication patterns in more intense violence, even though we do see that these communication patterns increase in magnitude as we increase the intensity of violence (e.g reduce the distance to violence or look only at events with fatality), further comparisons with large-scale battles would require better study of phone use during wars.

We should be clear on what this study does not speak to. First, this study does not attempt to study the causal impact of cell phone on violence. The causal impact of cell phone availability on violence has spawned a large literature.[5] For example, Shapiro & Weidmann (2015) carefully examine new cell towers sites in Iraq and find that communication networks is more valuable to locals trying to avoid violence than to insurgents attempting to perpetuate violence. However, Pierskalla & Hollenbach (2013) show that the new availability of cell phone services in Africa increases the probability of violent conflict. Our results cannot speak to the second. However, our results do suggest that, conditional on cell phone data being available, calls are taking on a different nature for tens of thousands of additional unique callers in the proximity to violence. This is consistent with the first. Second, we leave the challenge of using cell phone patterns to predict violence for future research.

This paper proceeds as follows: Section 2 explores the literature on cellphone usage and violence, leading into the development of our hypotheses. In section 3, we describe the data we use for violence, calls, and the geographic context. We also describe our estimation methods in this section. In section 4 we present the results of the estimation, showing how violence is different from other events. Section 5 concludes with a discussion of applications of the results of this paper to violence prediction.

2 Violence and Phone Usage

"Everyday" conflicts (Blair *et al.* (2014)) such as small-scale confrontations between militias (Autesserre (2010)), are not well-understood, despite their potential for escalation and their impact on national-level conflict (Balcells (2011)), reduced investment, and capital flight (Sambanis (2004), Lujala *et al.* (2005)). Kalyvas (2003) laments the difficulty of even understanding if these skirmishes occur randomly, an important question since complete unpredictability implies that the

[4] In fact, we observe more population movement around premier soccer matches than around low-level violence.

[5] A recent special issue of the Journal of Peace Research is focused on the causal effect of communications and information on conflict (see review of the ICT-political conflict research agenda Dafoe & Lyall (2015)).

target is indiscriminate and deterrence is impossible.[6] However, descriptions of involved parties often reveal that the community members might have anticipated or even participated in violence (Kalyvas (2003)).[9] Senaratne (1997) therefore argues that "the imputation of randomness by some observers (mainly journalists) was a result of (lack of information)."

The plethora of experiences that have been reported on, be it in the media, sociological interviews, or qualitative case studies, have relied on surveys, which Blattman (2009) notes, "suffer from a number of well-documented problems, including forgetfulness, 'telescoping', and simple dishonesty." Studies that measure observed behavior are not subject to these biases , however, they often focus not on behavior immediately surrounding the violent incident itself, but on behavior in the long term.[10] One exception is displacement (Kasara (2011)), which is an immediate goal and effect of violence. It is not clear, however, if displacement is a sensitive enough measure of anticipation since moving entails significant costs that may not be justified by the benefits of avoiding low level violence.[11] The ideal micro-level evidence to distinguish anticipation from surprise would be a moment-to-moment record of the local mood in the days before, during, and after the incident. This type of data is generally impossible to collect; however, the ubiquity of mobile technologies is quickly making this a possibility.

Psychologists have long documented that events serve as stimuli for positive and negative affect, both of which drives people to connect with others.[12] Mobile communication technology such as cell phones allows people to instantly act upon these needs, translating difficult-to-capture moods into call records. This suggests that the occurrence of a large, surprising event, will result in a sudden, widespread urge to communicate. In places where cell phones are the primary mode of communication, this would be observed as a sudden jump in call volume. Indeed, Bagrow *et al.* (2011) find huge spikes in calls in the immediate aftermath of plane crashes and earthquakes. We follow the literature in referring to this as the *jump-decay pattern* since this increase attenuates in the hours and days afterwards. Unlike the gradual increase ahead of scheduled events such as religious festivals and concerts (Figure 1), cell activity before surprising events are completely

[6]Indiscriminate violence is unpredictable and impossible to avoid. For example, "a German patrol ... arrested the first fifty persons who happened to walk down the street, lined them up against a wall and shot them out of hand." ([7]). Selective violence, in contrast, targeted people on the basis of their actions; [8] argues that this predictability is what makes selective violence better in inducing compliance.

[9]Information about violence appears to be dispersed among local residents at least post-violence: see Van der Windt & Humphreys (2014) on crowdsourcing reports of violence and Zeitzoff (2011) on mass twitter reactions.

[10]For example, Callen *et al.* (2014) looks at the link between risk preferences and exposure to violence.

[11]Seeing movement out of an area that will experience violence in the near future shows anticipation; however, lack of movement does not imply lack of anticipation

[12]The connection between crises and desire to seek social support have been replicated in circumstances as diverse as experimentally induced stress (Schachter (1959)), the Three-Mile Island nuclear accident (Fleming *et al.* (1982)), war combat, to personal tragedies (House *et al.* (1988)).

normal. Observing the jump-decay pattern in cell activity following low-level political violence will indicate that the event was a surprise.

Analyzing call activity may provide not only an indication of how surprised locals are by an event, but also a sense of whether their experience of it was positive or negative. Communication behavior after positive and negative stimuli is distinctly different from each other (Shea *et al.* (2015)). Negative experiences (e.g. those that induce uncertainty (Marshall & Zimbardo (1979)), helplessness, or anticipation of future negative events) drive people to seek emotional support and tangible assistance from those most likely to provide it (Thoits (2011)). As a result, this activates smaller, redundant social network structures. On the other hand, positive experiences facilitates approach behavior (Fredrickson (2001)), hence broadening social network. Consistent with these findings, Blumenstock *et al.* (2014) find that after earthquakes, people use mobile phones to reach out to those they share strong preexisting reciprocal links with and to those who are geographically closer to them. This is similar to what Cohen & Lemish (2005) observes after terrorist attacks and distinct from Pierskalla & Hollenbach (2013) study of rebel organizing where mobile activity is directed to geographically distant locations. A broadening of communication network before low-level violence will therefore suggest that locals are experiencing the event positively and/or through a position of control (instigator), while a narrowing of network that they are experiencing it in a position of insecurity (observer).

Following Bagrow *et al.* (2011), this paper will first look for the jump decay pattern around low level violence to establish whether the incident was a surprise to locals. Next we will look for evidence to distinguish whether the role of locals more closely resemble instigators or observers. Because the competition between mobile providers created discount plans for same network calls, family and friends are very likely to share the same network, in order to cut down on mobile costs. Therefore a shift towards within network calls (and phones that are closer geographically) will indicate a narrowing of communication networks, while a shift towards out of network calls (and phones that are more geographically distant) is consistent with the broadening of social network inherent in recruiting and coordinating. In addition, we speculate that urgent calls in a rapidly changing situation are likely to be shorter than the typical call to friends and family. We will also explore the movement of phones. An influx of phones (and therefore the owners of said phones) into an area before violence occur would suggest that outsiders are coming in, possibly as instigators. On the opposite, an outflow of phones would suggest that the threat of violence is clearly observable and severe enough for local residents to move out.

Because we largely focus on aggregate behavioral changes, it is important to remember that the same size effect can be a small number of people greatly changing their behavior or a large number of people making small changes in theirs. Drozdova & Samoilov (2010) explain how the process of planning violence would involve intensive communication among a small number of plotters. Therefore observing aggregate change in volume of calls and a broadening of communication network with no detectable change in the number of callers suggest the presence of instigators. On the other hand, an aggregate change in volume of calls that is accompanied by a narrowing of communication network and a large increase in the number of callers indicate widespread feeling of unease among ordinary citizens.[13]

Note however, that the relationship we are investigating here is not causal. It is entirely possible that tension created the conditions that made violence more likely. When an emotion is triggered it has an impact on our judgments as a consequence, we make choices in situations that tend to amplify our perception of risk (Lerner & Keltner (2001)). However, showing the correlation between the experience of locals and low level violence is an important first step since pre-event tension is a necessary condition for anticipation of violence.

3 Data and Methods

We explore our conjectures about behavior in the presence of violence by looking at two large sets of cellphone data from the Côte d'Ivoire. This section first presents a brief overview of the Côte d'Ivoire. Next, we describe the cellphone datasets in detail. Then we explain the data on violence. Finally, we detail our estimations strategy.

3.1 Geographic context

Côte d'Ivoire is a West African country of approximately 22 million. It was relatively peaceful and stable from independence in 1960 until civil wars broke out in 2002 and 2011, displacing over a million people and resulting in a persistently precarious security situation.[14] While there are national-level estimates of internal displacements by the Displacement Monitoring Centre and occasional news coverage of violent flare-ups, there is little systematic data about the life of the Ivorians at finer temporal and spatial levels.[15] However, the rapid growth of mobile phones in the period between the wars may provide a solution to the paucity of official data. By 2011, the Agence

[13] Note that because the number of instigators will be far smaller than the number of observers, it is very likely that signals from *observers* will swamp any possible signal from *instigators*. Thus if we observe *instigators* we can draw conclusions about the lack of *observers*, however, should we observe *observers* we cannot conclude whether or not *instigators* are also present.

[14] Readers interested in an in-depth treatment of the war are referred to McGovern (2011).

[15] The last census was in 1998.

de Télécommunications de Côte d'Ivoire) reported that there were 15.8 million mobile subscriber lines in the country, which translates to about three phones for every four Ivorians.

What sort of selection bias do we get in Côte d'Ivoire by using mobile phone data instead of survey data intentionally designed to be a representative sample? Aker & Mbiti (2010) look across Africa and conclude that while the initial adoption of cellphones was concentrated in the male urban middle class, this wealth and urbanization bias has disappeared. Further, Gillwald *et al.* (2010) show that by 2008 the gender gap in Ivorian phone ownership had become insignificant. Afrobarometer find that 92% of Ivorians have a cellphone in their household (further, some of those who do not own phones report having easy access to a phone) and 82% of Ivorians make at least one cellphone call per day. Mitullah & Kamau (October 2013) We are therefore confident that we are not missing a large swath of Ivorian society which has no access to phones. We find no evidence of systematic differences in pricing policy or subscriber base between the multiple mobile providers that operate in Côte d'Ivoire. Since calls between two SIM cards from the same provider (within-network calls) are cheaper than other calls, individuals with phones own on average 1.96 SIM cards (GSMA Intelligence (2012)) and switch between cards in order to minimize cross-network calling.[16]

Several aspects of the immediate post-war environment may amplify the sensitivity of day-to-day communication to incipient violence. First, the post-war environment could cause people to be more responsive to possible signs of violence than at other times.[17] Second, lingering internal displacement from the civil war could cause people to be more distant from family than in normal times, causing them to substitute telephone use for face-to-face communication. Using a case where the signal is at its strongest might normally raise questions of external validity since it is easier to detect even a very small effect. However, we believe that for this first attempt to relate real time cellular activity to small scale violence, any possible magnification of the effect is a feature.

3.2 Cellphone data

We examine two unique datasets from Orange Côte d'Ivoire, the second largest cellphone provider in the country. With a 25% market share, there were approximately 4 million Orange SIM cards in operation in 2011-2012.These datasets cover a 150 day period beginning on December 1, 2011 and ending on April 30, 2012. The first dataset, which we refer to as the *subscriber data*, consists the of

[16] We also have found no evidence that Orange customers are different from those of other providers in any systematic way. The Ivorian mobile provider market does not appear to be segmented by ethnicity or income, for example.

[17] Post-conflict situations are tenser in general (e.g. Hartzell & Hoddie (2003)). However, it is also possible that people become inured to conflict and therefore respond less to it. This would bias against our findings so we will not be concerned about this any further.

all calls made by a random sample of 500,000 unique cellphone SIM cards over the entire period. Phones which appear to be used for business purposes (such as by people who run communications stalls in markets) were excluded from the population from which this sample was drawn. (By limiting ourself to a single carrier, we can assume that each SIM is associated with a different individual.) While we have time and location of the call for each observation in this dataset, we have no information on the recipient of the calls. Subscribers locations are aggregated to the subprefecture level for privacy reasons. The data still follows pre-2008 organization, where the country was divided into 258 subprefectures (instead of 393 today). The second dataset is the *antenna data*. This dataset contains hourly records on total aggregate (directional) communications between pairs of Orange cellphones using Orange cellphone towers. This dataset is not a random sample, but a complete record of the total quantity of activity (number of calls and total time on the phone) between each pair of towers. This dataset does not include any calls where one or both callers is not an Orange subscriber, nor does it include calls where either the source or destination antenna belongs to a different provider. For the antenna location, exact longitudes and latitudes are provided. Mapping the 844 antennas to their corresponding subprefectures (dropping units that recorded no activity) gives 141 days of data of mobile activity from on average 3.59 antennas for each subprefectures.

Each record in the *subscriber data* contains a unique user ID, the caller's subprefecture, and time of call for any (both in- and out-of network) calls made by that subscriber.[18] We use the subscriber data to understand daily mobile activity at the subprefecture level. For this reason we will drop the largest city in the country, Abidjan, from our analysis. With a population of 7.1 million, Abidjan is an order of magnitude larger than other cities in the country, but is treated only as a single subprefecture in this dataset.[19] Since it is much easier to be unaware of tensions in a different district of a city of millions than in a different part of a village of thousands, we believe that physical distance to events impacts people in a qualitatively different way in a rural subprefecture than in Abidjan.

We generate four other variables from this dataset of 400 million calls. The first, *All Calls*, is the total number of calls from a given subprefecture on a given day. The second, *Active Subscribers*, is the number of different phones which register at least one call on a given day. We work with both these variables and their logged counterparts. We also generate a measure of mobility, *Moving in*,

[18] It is important to note that in this case a subscriber is a specific Orange SIM card. If someone owns two SIMs and switches between them depending on who she is calling, we only observe calls from the Orange SIM. Similarly, if they give, lend, or sell their phone to someone else who makes calls from it, we observe only one subscriber.

[19] The largest city not part of Abidjan is Bouaké, the North's largest city with a population of 650,000. No other cities have populations over 215,000.

which reflects the daily net flow of phones into each subprefecture. First, we define the location of a subscriber on date t as the subprefecture where she made her last timestamped call of the day. If a subscriber makes no calls, her location is defined to be the same as the previous day. For date t and subprefecture s, $Moving\ in_{s,t}$ is calculated as the difference between the number of subscribers assigned to location s on dates t and $t-1$ - in other words, the number of *net new* subscribers who moved into a subprefecture on date t. Finally, we generate *Nearby Percent* as the fraction of within-network calls made to phones within $0.5°$.

[TABLE 1 ABOUT HERE]

Table 1 Panel 1 presents a snapshot of these variables. A subprefecture records on average 12,203 calls from 1,293 different subscribers on an average day. Those 1,293 subscribers are a random sample of total subscribers; the 12,203 calls represent all the calls they make; each subscriber makes about 10 calls. Average net mobility is, reassuringly, approximately 0, as each subscriber who moves into one subprefecture is moving out of another. Violence (described in detail in the next subsection) is a rare event, affecting on average 1% of subprefecture-days. Therefore, think of the results as the responses of individuals in post-conflict Côte d'Ivoire to violence levels which occur in their area once every 3-4 months.

The *antenna dataset* is drawn from Orange's cell towers. This dataset provided us with hourly aggregate transmissions between each pair of Orange towers.[20] We collapse this to the day level in order to match the temporal resolution of our violence data.

We define three additional variables from this dataset. The first, *In-network Calls*, is the total number of calls made from a given antenna on a given day. Second, *Call Duration* is the average length of calls on a given day. Finally, *Daytime Call* $\%$ is the fraction of calls in a day made between 8 am and 5 pm.

Table 1 Panel 2 summarizes these variables. The average Orange antenna handles 2,830 Orange-Orange calls per day, which average 137 seconds apiece. This corresponds to a daily transmission of 5,772.83 minutes (96.2 hours) of conversation. While we do not know how many subscribers are making those calls, 64% of the calls are made during the day. The frequency of violence is similar whether we aggregate at an antenna level or a subprefecture level (1%), suggesting that there is no correlation between violence and antenna location. Comparing effect sizes across the two datasets requires care. The subscriber data represent all calls made by 500,000 random Orange subscribers. This is roughly one out of every eight Orange subscribers and one out of every sixteen mobile subscribers in Côte d'Ivorie. Generalizing from the antenna data is

[20]Since all cellular calls involve communication between phones and towers, this dataset could in theory contain information on all calls. However, Orange only provides calls between pairs of phones with Orange SIMs.

less straightforward. Orange has approximately a 25% market share, which means we may expect approximately $25\% * 25\% = 6.25\%$ of calls to be between two Orange towers. However, this direct scaling is questionable because within-network calls are much cheaper than between-network calls and hence, likely to make up a larger portion of overall calls.[21] Further, we do not capture calls which connect to non-Orange operated towers. We currently do not know what percentage of Orange calls involve non-Orange towers.

These two datasets provide complementary perspectives on calling patterns. The subscriber data demonstrates how individual callers change their calling patterns in response to violence. We can separate the intensity of calls from individual subscribers from the overall volume of calls coming from a subprefecture. This hints at whether changes in calls come from the intensive margin (e.g increased call frequency from active subscribers) or the extensive margin (e.g new activity from otherwise passive subscribers). However, it covers only about 12% of Orange subscribers. The antenna dataset captures all Orange-to-Orange calls. It contains average call durations, which may provide an indication of the function of the calls.[22] Finally, given its finer spatial resolution, the antenna data may be more suited for examining the comparative statics of change in calls given distance to violence.

3.3 Violence data

The most complete source of information about violence in Côte d'Ivoire during this period can be found in reports from the United Nations Operation in Côte d'Iviore (UNOCI, or ONUCI in French). "ONUCI hebdo" (UNOCI weekly) is a weekly summary of events in Cote d'Ivoire, with a focus on the actions, concerns, and effects of the UN post-conflict peacekeeping mission. Since UNOCI has a mandate to focus on the post-crisis situation, this effectively filters for political violence. Therefore, they do not report the vast majority of violence, which is made up of assault, robberies, or even murders which do not relate to the political situation. The only source for such data would be Ivorian police records which will vary greatly in quality across time and space. There are no incidents of high-level violence (battles, massacres, or the like) during the period for which we have data, so all inferences we make will be about low-level violence. While we might be concerned that the UN would avoid the most violent areas, thus missing the very areas we are most interested in, evidence from Ruggeri *et al.* (2013) shows that UN peacekeepers focus on areas where the conflict has been historically most explosive. They also describe the process through

[21] Indeed, Orange-Orange calls average 9,343 calls/day/subprefecture; suggesting that 76% of calls are in-network calls.

[22] For example, emergency calls are likely to be shorter than social calls.

which the UN records violence. Events are reported up from local-level employees to district managers and then on to regional managers. This gives significantly more uniform coverage than newspaper reports, especially the foreign press, who tend to be much more focused on the capital and large cities.

We code all cases of violence in UNOCI weekly that includes a specific location. This excludes general events (there are reports of tensions along the Liberian border) and violence that is not sufficiently large and political to be reported by the United Nations. We include cancellation of voting due to intimidation or threatened violence even if no violent acts are actually committed. The resulting list includes 44 incidents of violence. These are not the large artillery battles of the first Ivorian civil war or even battles where hundreds died such as in the second Ivorian civil war. Instead they include two people being killed in an ethnic clash, one person being killed and property damaged in an attack on civilians, and post-election tension and irregularities which caused a local vote to be annulled and rerun. For robustness we later distinguish between events that resulted in fatalities from those that do not. The UN usually records the exact date of violence, but is occasionally ambiguous about exactly on which day an event occurred. Our core specification uses only those events where we know the exact date, though we conduct robustness checks by using any clues in the descriptions to guess the exact dates of the remaining events. A complete list of violent events, dates, locations and descriptions is available in the online appendix.

The UN records a range of different types of violent events. Some look very much like small versions of traditional measures of violence, such as the 6 people killed in conflicts between the army and local residents in Vavoua. Others are clearly political, but do not involve deaths, such as the election day intimidation and violence which caused elections in Bonon district to be postponed. Some, such as clashes between herders and farmers inhabits the space of targeted violence during political unrest that Kalyvas (2003) worries is missed in studies of conflict. While there is heterogeneity in these events, this reflects the real world heterogeneity of types of violent events. It is preferable to continue to work with these events and risk having our estimates biased towards zero than to try to second guess the UN in determining what events were "sufficiently political" for us to include.

[FIGURE 3 ABOUT HERE]

The dates and locations of violence are shown in Figure 3. While the events are spread over the entire time period, there are a few major events which affect the entire country. There are parliamentary elections on December 11, 2011 which cause in widespread violence. In late January and early February the football team were runners up in the Africa Cup of Nations, during which violence was generally down. The coup on March 21 and ensuing civil war in neighboring Mali did not lead to significant refugee flows into Côte d'Ivore, but Ivorian refugees in Mali were returned home. However, ONUCI does not report observing outbreaks of violence in response to this event.

Violence is more likely to occur on some days of the week than others. Sundays are by far the bloodiest day of the week, accounting for 62.25% of violent events. This pattern is exacerbated by the fact that the most violent day in our sample is election day, a Sunday. Monday is the second bloodiest, with 24.14% of all events. Thursdays and Fridays account for the remaining 13.61% of violent incidents. We are mindful of the need to consider the Sunday-Monday effect in what follows.

To connect the UNOCI data with the cellphone data we generate an indicator for subprefectures and antennas which are close to violence. For each subprefecture s and date t, we define a binary variable V_{st} which is 1 if a violent incident is recorded by UNOCI as occurring exactly on date t and within $0.5°$ (35 miles) of the centroid of subprefecture s.[23] The mapping for the other dataset is straightforward, as for each antenna i and date t, we define a binary variable V_{it} which is 1 if a violent incident occurred within $0.5°$ (35 miles) of antenna i on that date.[24]

The other natural sources of data are the Uppsala Conflict Data Program (UCDP) and the Armed Conflict Location and Event Data Project (ACLED). Our definition of violent event is similar to, but slightly more general than, that used by UCDP. The UCDP dataset also terminates before the end of our cellphone data. We include events without any deaths as well as fatal incidents. While UCDP explicitly limits themselves to violence related to conflict, we are implicitly limited to conflict-related violence due to UN procedures. Reassuringly, for the period where the datasets overlap the UN data is a superset of the UCDP data, and our *Fatal Violence* variable (described later) is identical to the UCDP data. ACLED is very different from both UCDP and the UN data. Events which both the UN and UCDP place well outside the capital are placed in Abidjan, and some events we observe are either omitted or subsumed in reported events on nearby dates in other parts of the country. For these reasons we avoid using ACLED data.

3.4 Empirical Strategy

We present a series of regressions of the call variables presented in section 3.2 on the violence measures described in section 3.3. The data are nested both in time and space. Antennas, indexed by i, are nested in subprefectures, indexed by s, which are further nested in region, r. Similarly, days are indexed t, and are nested in days-of-the-week (e.g Monday, Tuesday), w. We subscript

[23] In the analysis, we will vary distances to $0.25°$, $0.75°$, and $1.0°$. We will also vary the precision of the recorded event date and the intensity of the event (fatal or not).

[24] Note that the decision to primarily measure distances in degrees as opposed to kilometers or miles makes no difference.

variables with the finest level at which they vary.[25] Call-related variables on day t are thus c_{it} or c_{st}, depending on whether we are working at the antenna i or subprefecture s level.[26] Our core specification of ordinary least squares with two-way fixed effects with standard error clustered on the geographical units in Eq 1 and Eq 2 is thus:

$$c_{it} = \alpha_i + \sum_{D=-L}^{+L} \beta^D V_{it}^D + \delta_{rt} + \epsilon_{it} \tag{1}$$

$$c_{st} = \alpha_s + \sum_{D=-L}^{+L} \beta^D V_{st}^D + \delta_{rt} + \epsilon_{st} \tag{2}$$

Our main independent variables are V_{it}^D and V_{st}^D. Recalling Section 3.2, these variables indicate whether a given antenna or subprefecture centroid was near a violent event exactly D days from date t. We initially define *near* as $0.5°$ (35 miles) away and later vary this distance to confirm that the effects attenuate with distance to violence. Negative values of D indicate future violence, while positive values indicate past violence. The parameters of interest are the β^Ds, which represent changes in call activity in a given location exactly D days after violence. Significant β^D for $D < 0$ indicates anomalies in communication behavior ahead of violence, significant β^0 indicates changes during the violent incident, and β^D for $D > 0$ indicates changes after the incident.

To determine the optimal number of leads and lags $(-L, +L)$ for the main independent variables, V_{it}^D and V_{st}^D, we start by considering an eight day window $(-8, +8)$ around the violence and then shrink the window one day at a time. For each specification we then test the joint hypothesis that there is no change in the coefficient more than n days before the violence.[27] For leads of more than 4 days, we cannot reject the null hypothesis that the coefficients are jointly 0 in 9 of the 10 tests. However, once we include the fourth lead it becomes hard to reject the null. Therefore in the regression tables that follow we will use a constant 4 day window around events.

In considering controls for time, we take into account several facts about Côte d'Ivoire. First, violence is concentrated on certain days of the week. Second, certain days of the year experience

[25]Thus, day fixed effects are δ_t while day-of-week fixed effects are δ_w, instead of referring to both as δ_{tw}.

[26]It is initially plausible that the correct specification includes a lagged dependent variable rather than a static model with fixed effects. To check for this, we first looked at the within-unit autocorrelation of the call variables and test for unit root. We find no higher order autocorrelation and the Dickey Fuller test rejects the null of a unit root convincingly. We see clear evidence of minor first-order autocorrelation, significantly less than 0.3, and no higher order autocorrelation. The Dickey Fuller test returns an inverse $\chi^2(1682)$ of 23,500, against a 0.001 probability level of 1,867. Alternative specifications with lagged dependent variables and with time trends as well as regional time trends are available upon request.

[27]We shrink the window down to $(-3, +3)$ and jointly test the coefficient for $n =$ to 3. Concerns about multicollinearity should be assuaged given that removing variables in the restricted model leaves the remaining coefficients and standard errors almost untouched. Tables are available upon request.

shocks common to the entire country (e.g, Election Day, African Cup of Nations football matches, holidays). Third, observances like Christmas are more important event in the Christian south than the more Muslim north. We therefore use day-region fixed effects, δ_{rt}, which are day dummies interacted with region dummies. They account for regular weekly patterns which can be the same or different in different regions in addition to shocks common to the entire country while allowing individuals in the two regions to respond differently to events. Time-invariant characteristics of the units (e.g. area) are captured by the unit fixed effects, α_i or α_s, which also implicitly control for slow-changing correlates of phone use, such as population density.[28]

4 Results

Behavior changes in proximity to violence. In the first subsection, we show that the behavior in reaction to violence is consistent with either *observers*. The second subsection separately considers how calling changes in proximity to football matches and major festivals. The final subsection demonstrates that the estimates are robust to a range of specifications and that varying the distance to violence and the incident intensity has the expected effects on the magnitudes of estimates.

4.1 Core results

Table 2 examines the subscriber dataset. The first four columns consistently show that low-level violent events are correlated with detectable changes on the ground. The first column demonstrates that there is a both statistically and substantively significant increase in number of calls in the days preceding violence.[29] There are anywhere from 1143 to 1927 additional calls per day in the sample.[30] This represents a $9.7\% - 14.1\%$ increase in daily call volumes (Column 2). Columns 3 and 4 show a similar pattern for active subscribers: there are $6.4\% - 7.6\%$ more individuals than usual are making calls in days leading up to violence. Columns 1 to 4 show that the largest increase happens on the day of the violence. This is consistent with communication that reflects the anticipation and the experience of an incident. Even though some of these coefficients remain significant on the first and fourth day after the incident, a joint F-test cannot reject the null of no post-violence changes (p-value 0.2809). However, we can reject the null for pre-violence cell usage (p-value 0.0216). Column 5 shows that the level of fear due to potential anticipation of

[28]Official population estimates far predate the civil wars: the last census was conducted in 1998.

[29]See Figure 4 Panel A for call volume changes before and after incidents.

[30]Assuming that we have a random sample of the 8 million cell subscribers, this is equivalent to $18 - 30$ thousand additional daily calls leading up to a violent incident.

these events is limited: there is no significant change in the number of people entering or leaving a subprefecture before violence.

The first four columns are completely inconsistent with the events being totally unanticipated. Calls and callers both increase well before the violence, and attenuate quickly after the violent events. While Columns 1 and 2 (increase in calls) would be consistent with both naive observers and instigators, the huge increase in unique callers Columns 3 and 4 strongly favors an interpretation involving observers over one mostly driven by instigators. Finally, Column 5 (mobility) is consistent with observers who believe that the danger that they will be killed is limited.

[TABLE 2 ABOUT HERE]

Table 3 proceeds to the antenna dataset. The first two columns examine the daily volume of calls transmitted between pairs of Orange towers. Therefore, they are picking up only *within-network* calls as opposed to *All Calls* from Table 2. While there is a lot of noise in Column 1, Column 2 shows a significant increase in calls before violence (14.7%-19.2%), peaking on the day of violence (25.6%) before attenuating after the violence (7.18%). Column 3 shows that the duration of calls *decreases* by 4.9 to 8.2 seconds before violent incidents. Since average calls are 137 seconds long, this corresponds to a 3-5% decrease in duration (Column 4).[31] Column 5 checks whether the timing of calls shifts in proximity to violence. There are more night time calls on $D = \{-3, 3\}$ and more day time calls on $D = \{-1, 0, 1\}$, but these coefficients are extremely small in magnitude.

Similarly to Table 2, we can see significant changes in phone use before violence, which again strongly suggests that local residents are not surprised. The increase in nearby calls is strongly consistent with observers but not instigators. Similarly, the decrease in call length agrees with the pattern expected of naive observers, but not with that expected of the other possibilities. Finally, we observe a minor shift towards more daytime calls. In sum, we are further convinced that observers presents the best description of the circumstances ahead of violence.

[TABLE 3 ABOUT HERE]

Table 4 utilizes variables from both datasets to understand mechanisms behind these changes. Column 1 introduces a control for the number of active subscribers into the specification from Table 2 Column 1. We see that each active subscriber makes approximately 15 calls per day. Contingent on this, there is no additional increase in volume of calls due to violence. Switching to a logged specification does not substantively affect the results (Column 2). However, Column 3 shows that even accounting for active subscribers, there are increases in win-network calls ranging from 7.3% to 11.7% before violence to a peak of 13.3% on the day of violence. This increase holds

[31] Figure 4 Panel B plots call duration changes before and after incidents.

even when we account for the total call volumes in each subprefecture (Column 4). This behavior suggests that calls are shifting to those with whom one shares a mobile provider.[32]

In Columns 5 and 6, we investigate whether shorter call duration can be explained by physical limitations in communications infrastructure as opposed to behavioral changes. Though coverage is generally good across the country, higher utilization (such as due to more active subscribers or larger volume of calls) can overcrowd networks causing dropped calls. The last two columns of the table show that, consistent with expectations, higher utilization is associated with shorter calls. However, the decreased call length is more than what can be explained by network congestion. Overall, the behavior appears consistent with citizens shifting their mobile usage towards urgent calls to close friends and family in anticipation of future violence (and due to the immediate experience of violence). Interestingly, Columns 3-6 show that the largest magnitude of pre-incident changes occurs two days before the incident.

Yet again, any changes we observe begin well before violence. The shift to more within-network calls is once again consistent with observers, but not with instigators who are trying to mobilize large numbers of people. Further, the stability in calls per caller is similarly inconsistent with instigators.

[TABLE 4 ABOUT HERE]

The key results from this section can be seen graphically in Figure 4. Panels A and B individually show the increase in calls along with the decrease in call duration associated with violence. Panel C displays the extent to which the additional calls are driven by more callers as opposed to more calls per caller. Finally, the divergence between all calls and in-network calls is demonstrated in panel D.

[FIGURE 4 ABOUT HERE]

4.2 Other types of events

In order to better understand the behavior around violence, we now compare the call patterns around violence to that around other types of events. This is important both in order to demonstrate that patterns around scheduled events don't also conform to the pattern of naive observers (which would suggest that we have an incorrect understanding of naive observers) and to show that we are not mistaking known events which might cause excitement, and therefore violence, for actual violence.

In Table 5 repeats the main specifications from Tables 2 and 3 with local football matches as the key independent variable instead of violence. We use matches from the Côte d'Ivore Ligue 1,

[32]Figure 4 Panel C illustrates this shift to in-network calls.

the top division of Ivorian domestic football clubs. There are clubs in this league from across the country, allowing us to exploit both the temporal and geographical variation in the occurrence of matches. In the first two columns, we observe a (sometimes statistically significant) decrease in calls and unique callers. Column 3 shows no strong movement patterns, with sign and significance switching between rows. In Column 4, we again see more calls and column 5 shows in increase in call durations. Finally, we see fewer local calls in column 7.

[TABLE 5 ABOUT HERE]

This is clearly very different from the pattern in advance of violence. We observe opposite opposite changes in call volumes, callers, duration, within-network percentage and percent of calls nearby. Clearly we are not confusing football or football-like events for violence. Similarly, we are not observing what we think of as naive observer behavior in advance of easily-predictable events.

Table 6 we consider the specifications from Table 4. Again, we can observe that the pattern is quite unlike that around violence. Most strikingly, we can observe that unlike the shift within-network around violence, there is a shift to more between-network calls around football. Similarly, fewer calls are made nearby around football matches, again opposite of the violence result. This suggests that any shift in calls is towards calling looser acquaintances to catch up about the match, rather than high-importance calls to close friends and family.

[TABLE 6 ABOUT HERE]

Along with Table 5, this shows an easily interpretable set of behavior around football games. In general, even the first division of the domestic league is not a huge enough issue to cause major increases in call volumes. Many fewer people are involved than those who are impacted by the changes ahead of violence. Those who do care about the games are talking to their friends about the game, leading to longer calls, mostly to those who are not local, likely friends who follow the other team. There is no reason to expect these to be close friends, which is why we see a shift out of the network.

Next, we consider how calls change ahead of major festivals. These are national events including religious observances such as Christmas and Eid and secular holidays such as New Year's Day and Labour Day. In Table 7 we are forced, by the fact that most major festivals take place nationwide, to relax the day-region fixed effects, instead including a complete set of day-of-week dummies along side week fixed effects. We observe an huge increase in calls from two days before the festivals until the day afterwards. This is an increase in both calls and unique callers. Unlike violence, we see a significant increase in calls per caller, and no common pattern of changes in within versus between network calling. In other words, people are calling similar sets of people as they normally call, but each person is making many more calls than they would on a normal day.

[TABLE 7 ABOUT HERE]

The difference between violence, football, and festivals can be seen visually in Figure 5. Looking at the three panels, it is visually striking how the response to violence starts far before the event and then decays once the violence occurs. Football has some small changes in the opposite direction as violence continuing well after the violence. Festivals have a third distinct signature, while the change in response to festivals spikes the day before the festival before plateauing.

4.3 Robustness

Table 8 explores the effect of varying the distance to violence (V_{it}^{D}). If changes in communication are due to the threat of violence or something strongly correlated with it, we expect attenuated responses in calling behavior as the distance from violence increases. We first investigate the finer spatial resolution antenna data (*log(Within-Network Calls)* in Column 1-4) before confirming it with subprefecture data (*log(Active Subscribers)* in Column 5-8). Column 1 cuts the radius in half to 0.25 degrees (18 miles). This reduces the number of affected antennas by 75%, which leads to a complete loss of statistical significance. Column 2 is our base specification of a 0.5 degree (35 miles) radius. Column 3 increases the radius to 0.75 degrees (53 miles). The coefficients are attenuated, as areas farther from the violence are added. Finally, Column 4 increases the radius to 1 degree (70 miles), which further attenuates the effects. The sub-prefecture data follow a similar pattern, as reported in columns 5-8.[33]

[TABLE 8 ABOUT HERE]

Table 9 explores the effect of varying the type of violent events we include in V_{it}^{D}. In Column 1, we expand our coding of violence to include violent events whose exact dates are uncertain. The magnitude of the effect of violence is lessened and spread out over more dates, as expected from the addition of events with dates measured with random error. In Column 2, we return to our core specification, considering all violent events, both fatal and non-fatal, where the date is measured precisely. Column 3 only includes fatal events, whether or not we are certain of their exact date. The magnitude of the effects is significantly larger, which makes sense if people react more strongly to the sorts of situations which can lead to fatal events. Column 4 shows that by restricting the sample to fatal events with precise dates the magnitudes of the events are the largest. Again, columns 5-8 show that results are similar using number of log(active subscribers) as the dependent variable.

[33] These results also demonstrate that there is no unit-of-analysis issue. Since the effect attenuates smoothly as we look at larger areas rather than jumping around and switching signs, it is unlikely that the results we are seeing are an artifact of a particular choice of radius.

[TABLE 9 ABOUT HERE]

5 Conclusion

Low-level political violence occurs in many developing and consolidating democracies. We use fine-grained cellphone records to examine how individuals behave before and after such events whose unpredictability has in the past been a serious barrier to studying. We observe the behavioral patterns around violence, football matches and festivals. In the days leading up to violence call volumes increase, driven by a larger number of individuals making calls, while the average duration of said calls decreases. Furthermore, the percentage of calls to people who are physically close increases along with the percentage of calls to people who share the same carrier. This implies that people are communicating about the possibility of the upcoming violence with friends and family in advance of such an incident occurring.

In this paper, we show that in Côte d'Ivoire, people change their behavior in advance of violence in a predictable way. The fact that Low-level political violence can be clearly anticipated in advance strongly implies that even seemingly random small violent events are actually , leading locals to intensify contact with friends and family in advance of the occurrence of events. This is in agreement with the observation of Kalyvas (2003) that apparently random low-level violence is actually targeted, and in direct contrast to what we know of terrorist attacks, which are distinguished primarily by the fact that they are unanticipated.

In this paper, we find that one can distinguish between violence and exciting events. We also observe that low-level political violence produces a reaction greatly dissimilar to other exciting local events. The communications signature for low-level political violence looks totally unlike that of football or festivals, which can further be clearly distinguished from each other. This strongly implies that the type of low-level political violence that we study here is not simply a case of emotions running high in otherwise exciting periods, but a phenomenon of its own type.

This paper also speaks to work such as Arriola & Travaglianti (2015) which shows that large fractions of the population claim that they fear being targets of political violence, and find some demographic characteristics which predict which sorts of individuals will claim to fear being victims of political violence. One major concern is that individual perceptions of the probability of being targeted are biased. In this paper, we show that there are actual changes in behavior in the areas where political violence is likely to occur, which is consistent with the link these authors draw between perceptions of threat and actual threat.

The approach in this paper suggests natural avenues for future work. Previously, it was difficult to think about how we should classify different types of violence. Much of the literature has focused on situations with large death counts, which may or may not lead to larger but otherwise similar behavioral responses as low-level violence. Kalyvas (2008) explicitly worries that using standard datasets which focus on massacres miss the qualitatively distinct low-level violence. Where do quantitative differences in intensity or notice become qualitative differences in type of violence? Communications data give one possible answer. As the size of the violent events we observe increase, the call patterns we observe intensify, but do not change. However, there are no battles in the period we observe, so the largest violent events we see are smaller than the smallest that many papers consider. Future work could determine the size of event at which the behavioral signature changes, which would be a natural break-point for categorization.

Finally, the communications signature in this paper has significant implications for future work in violence prediction. The current state of the art, such as Weidmann & Ward (2010), are still limited to prediction at the provence-month level. Blair *et al.* (2014) are able to use surveys to predict violence in Liberia at the village level, but do not attempt to make temporal predictions. While prediction is beyond the scope of this study, this paper discovers a signature of violence which promises to be useful for high-precision prediction in the future. This suggests that violence can be predicted at a much higher level of precision than in previous work. Future prediction based on these results promises to have important implications for real-world activities such as election monitoring and peacekeeping.

While this is the first use of cellphones in the study of low-level political violence, we are confident it will not be the last. By allowing us a window into an important but difficult-to-study phenomenon, we better understand how individuals react to one of the most common forms of violence in the world.

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Figure 1: Calling responses to various events. Reproduced from Bagrow *et al.* (2011)

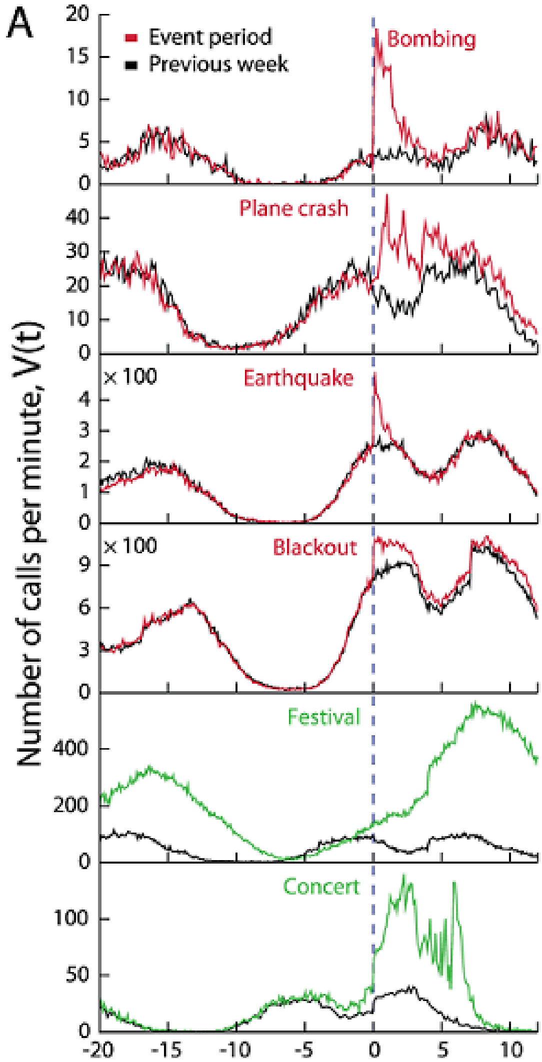
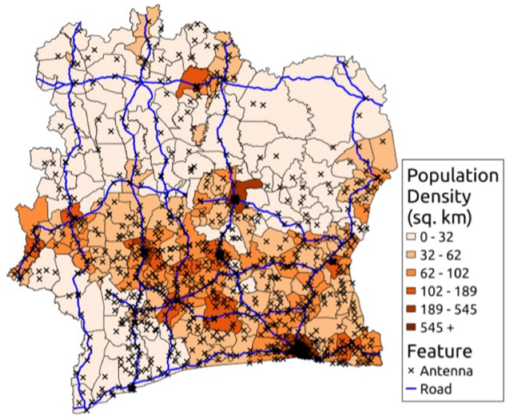


Figure 2: Population density and Mobile Phones in Côte d'Ivoire



. Reproduced from Zheleva *et al.* (2013)

Figure 3: Violent Events

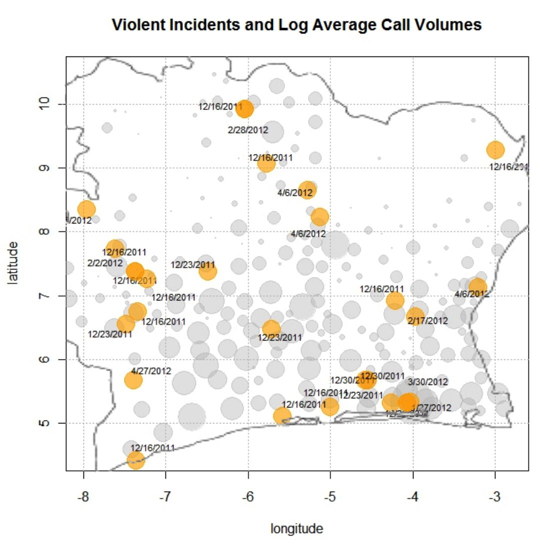
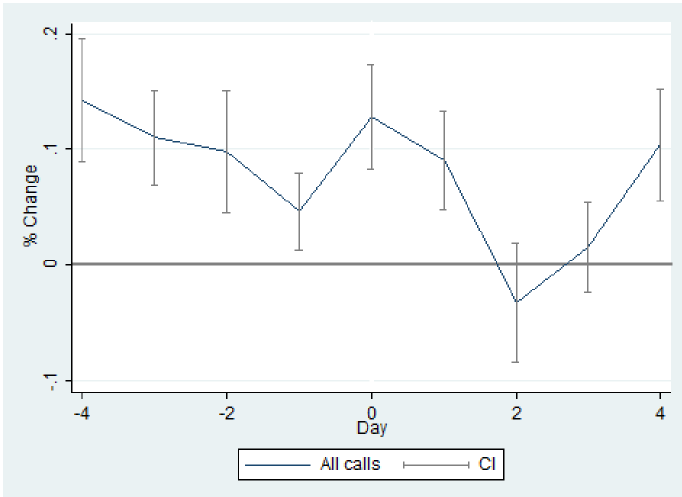
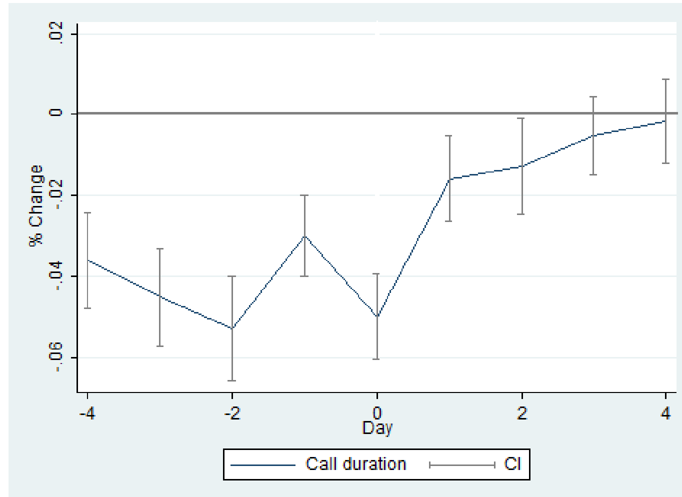


Figure 4: Behavioral response to violence

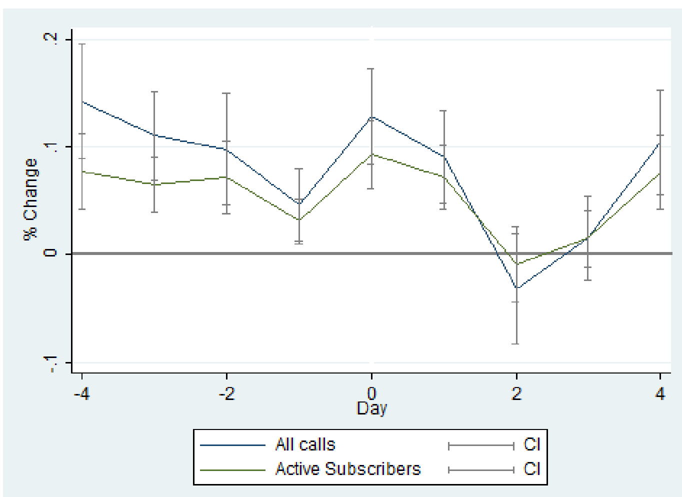
Panel A: Percentage Change in Call Volumes



Panel B: Percentage change in Average call durations



Panel C: Calls and Callers



Panel D: All calls vs. in-network calls

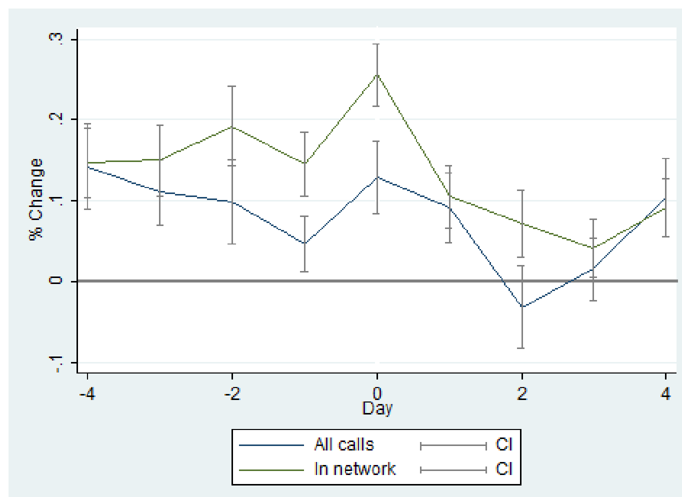
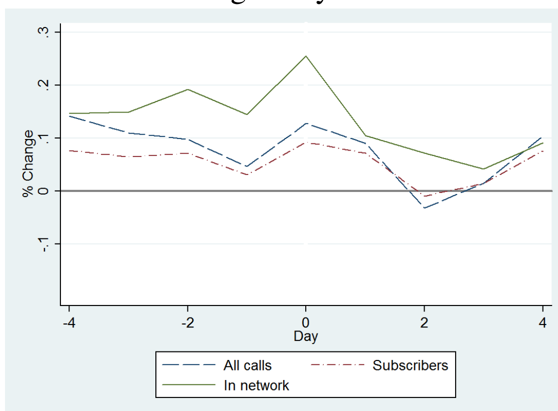
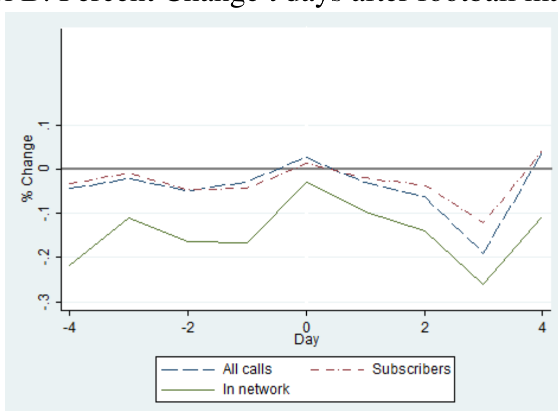


Figure 5: Comparison of behavioral responses to violence, football, and festivals

Panel A: Percent Change t days after violent incidents



Panel B: Percent Change t days after football matches



Panel C: Percent Change t days after national festivals

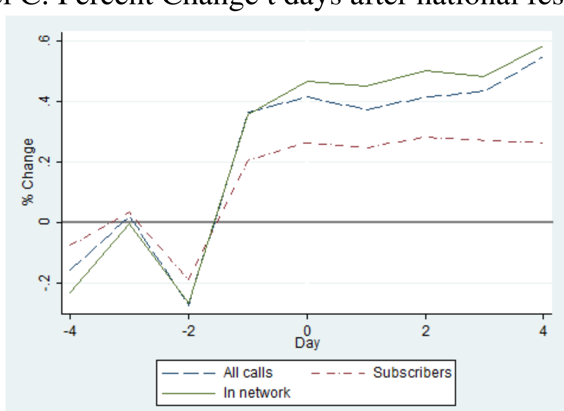


Table 1: Summary Statistics

Panel 1: Subscriber Data

	mean	sd	min	max
Days with calls	140.72	9.45	72	144
All calls	12203.24	22153.95	138.0	197485.7
log(All calls)	8.284	1.4734	4.7289	12.139
Active subscribers	1292.659	1830.953	19.699	12237.31
log(Active subscribers)	6.159	1.423	0	9.2618
Moving in	.6958	2.722	-7.131	22.717
Fraction days near violence	.01035	.01114	0	.0534
n=233				

Panel 2: Antenna Data

	mean	sd	min	max
In-network calls	2830.161	2625.014	44.77	21012.4
log(In-network calls)	7.299	.917467	3.05	9.833
Call duration (sec)	137.2698	21.7225	82.5086	241.882
% calls made during the day	.64158	.0366	.44336	.8988
Fraction days near violence	.01081	.01324	0	.0625
n=844				

Table 2: Subscriber data: mobile phone usage around violent incidents

	(1) All Calls	(2) log(All Calls)	(3) Active Subscribers	(4) log(Active Subscribers)	(5) Moving in
4 Days Before	1927.2**	0.142***	92.19*	0.0769**	-7.709
	(862.9)	(0.0532)	(55.01)	(0.0346)	(7.580)
3 Days Before	1143.2**	0.110***	71.48**	0.0647**	-2.226
	(497.0)	(0.0406)	(35.14)	(0.0255)	(4.770)
2 Days Before	1471.3**	0.0978*	112.2**	0.0717**	-1.588
	(711.4)	(0.0523)	(55.87)	(0.0341)	(3.618)
1 Day Before	1331.8**	0.0464	78.84***	0.0307	5.384
	(583.4)	(0.0335)	(29.66)	(0.0209)	(4.601)
Day of Violence	1563.8***	0.128***	120.2***	0.0926***	-0.214
	(591.4)	(0.0449)	(45.22)	(0.0315)	(2.610)
1 Day After	1211.1	0.0905**	94.02**	0.0717**	0.887
	(789.6)	(0.0429)	(46.72)	(0.0295)	(2.948)
2 Days After	463.6	-0.0319	35.92	-0.00931	-2.848
	(496.4)	(0.0513)	(28.28)	(0.0347)	(3.497)
3 Days After	1327.4	0.0150	29.53	0.0145	1.248
	(843.5)	(0.0388)	(35.97)	(0.0259)	(2.679)
4 Days After	1432.1**	0.104**	81.86**	0.0762**	-2.731
	(577.0)	(0.0479)	(39.57)	(0.0343)	(2.827)
N	28473	28473	28473	28473	28473

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Antenna data: mobile phone usage around violent incidents

	(1) log(In-Nwk Calls	(2) In-Nwk Calls	(3) log(Call Duration)	(4) % Calls Daytime	(5) Calls to Nearby Phones
4 Days Before	0.147***	-6.109***	-0.0361***	-0.000170	0.0481***
	(0.0428)	(1.725)	(0.0118)	(0.00185)	(0.00914)
3 Days Before	0.150***	-7.157***	-0.0452***	-0.00989***	0.0470***
	(0.0441)	(1.648)	(0.0119)	(0.00305)	(0.00909)
2 Days Before	0.192***	-8.213***	-0.0529***	-0.00376	0.0465***
	(0.0497)	(1.869)	(0.0130)	(0.00296)	(0.00956)
1 Day Before	0.145***	-4.910***	-0.0299***	0.00781**	0.0289***
	(0.0392)	(1.506)	(0.0100)	(0.00312)	(0.00711)
Day of Violence	0.256***	-8.742***	-0.0499***	0.0174***	0.0341***
	(0.0388)	(1.613)	(0.0107)	(0.00260)	(0.00716)
1 Day After	0.105***	-3.725**	-0.0159	0.0128***	0.00173
	(0.0382)	(1.574)	(0.0106)	(0.00308)	(0.00769)
2 Days After	0.0718*	-2.046	-0.0128	0.00490*	0.00603
	(0.0410)	(1.642)	(0.0118)	(0.00275)	(0.00816)
3 Days After	0.0417	-1.843	-0.00519	-0.00612***	-0.00112
	(0.0359)	(1.428)	(0.00966)	(0.00189)	(0.00732)
4 Days After	0.0916**	-1.034	-0.00155	-0.00131	-0.0000200
	(0.0359)	(1.536)	(0.0104)	(0.00298)	(0.00747)
N	94227	94227	94227	94227	94227

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Who Makes the Additional Calls?

	(1) log(All Calls)	(2) log(In-Nwk Calls)	(3) log(Call Duration)	(4) Calls to Nearby Phones
4 Days Before	0.0362^{**}	0.0201	-0.00769	0.0295^{***}
	(0.0160)	(0.0338)	(0.00647)	(0.00505)
3 Days Before	0.0210	0.0159	-0.0163^{**}	0.0281^{***}
	(0.0156)	(0.0343)	(0.00683)	(0.00491)
2 Days Before	-0.000842	0.0751^{**}	-0.0159^{**}	0.0223^{***}
	(0.0156)	(0.0378)	(0.00735)	(0.00458)
1 Day Before	0.00420	0.0748^{**}	-0.00193	0.0106^{***}
	(0.0127)	(0.0309)	(0.00605)	(0.00335)
Day of Violence	0.000793	0.0938^{***}	-0.000604	0.00184
	(0.0132)	(0.0359)	(0.00665)	(0.00374)
1 Day After	-0.00815	0.0441	0.00432	-0.0115^{***}
	(0.0134)	(0.0297)	(0.00652)	(0.00436)
2 Days After	-0.0191	0.0438	0.00107	-0.00303
	(0.0118)	(0.0303)	(0.00851)	(0.00529)
3 Days After	-0.00491	0.0187	0.00284	-0.00638
	(0.0155)	(0.0263)	(0.00585)	(0.00419)
4 Days After	-0.000975	0.0240	0.0161^{***}	-0.0116^{***}
	(0.0152)	(0.0290)	(0.00605)	(0.00429)
Active Subscribers	1.375^{***}			
	(0.0295)			
log(All Calls)		1.204^{***}		
		(0.148)		
log(In-Nwk Calls)			-0.192^{***}	0.126^{***}
			(0.00321)	(0.00163)
N	28473	94227	94227	94227

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Antenna data: mobile phone usage around local football

	(1) log(All Calls)	(2) log(Active Subscribers)	(3) Moving In	(4) log(In-Nwk Calls	(5) log(Call Duration)	(6) % Calls Daytime	(7) Calls to Naerby Phones
4 Days Before	-0.0441**	-0.0323***	15.10*	-0.218***	0.0338***	-0.0252***	-0.0325***
	(0.0188)	(0.0123)	(8.407)	(0.0160)	(0.00535)	(0.00202)	(0.00245)
3 Days Before	-0.0214	-0.00853	15.93	-0.111***	0.00853	-0.00140	-0.0167***
	(0.0233)	(0.0160)	(11.13)	(0.0139)	(0.00590)	(0.00188)	(0.00165)
2 Days Before	-0.0484***	-0.0461***	4.597	-0.165***	0.0266***	-0.00731***	-0.0233***
	(0.0139)	(0.0113)	(5.628)	(0.0114)	(0.00508)	(0.00162)	(0.00182)
1 Day Before	-0.0281	-0.0428**	-8.441	-0.166***	0.0824***	-0.0137***	-0.0208***
	(0.0269)	(0.0195)	(5.761)	(0.0141)	(0.00787)	(0.00214)	(0.00199)
Day of Football	0.0265	0.0127	-5.327	-0.0299***	-0.00625	0.0463***	-0.0135***
	(0.0177)	(0.0141)	(6.884)	(0.00984)	(0.00567)	(0.00324)	(0.00168)
1 Day After	-0.0304*	-0.0197*	-15.70**	-0.0978***	0.00435	0.000176	-0.0148***
	(0.0171)	(0.0119)	(6.386)	(0.0120)	(0.00542)	(0.00178)	(0.00175)
2 Days After	-0.0622***	-0.0360***	15.04**	-0.141***	0.0207***	-0.0115***	-0.0210***
	(0.0170)	(0.0111)	(6.861)	(0.0114)	(0.00567)	(0.00192)	(0.00191)
3 Days After	-0.190***	-0.121***	-14.06*	-0.260***	0.0724***	0.00556***	-0.0260***
	(0.0304)	(0.0244)	(7.535)	(0.0161)	(0.00798)	(0.00210)	(0.00213)
4 Days After	0.0402*	0.0423***	14.09*	-0.107***	0.00782	-0.00126	-0.0226***
	(0.0219)	(0.0160)	(8.432)	(0.0151)	(0.00635)	(0.00183)	(0.00223)
N	28473	28473	28473	94227	94227	94227	94227

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Who Makes the Additional Calls around football?

	(1) log(All Calls)	(2) log(In-Nwk Calls)	(3) log(Call Duration)	(4) Calls to Nearby Phones
4 Days Before	0.000983	-0.127***	-0.00809*	-0.00504***
	(0.0114)	(0.0178)	(0.00489)	(0.00185)
3 Days Before	-0.00947	-0.0855***	-0.0128***	-0.00273*
	(0.00978)	(0.0129)	(0.00480)	(0.00157)
2 Days Before	0.0159	-0.111***	-0.00515	-0.00251*
	(0.0108)	(0.0123)	(0.00456)	(0.00150)
1 Day Before	0.0316***	-0.0930***	0.0504***	0.000107
	(0.00848)	(0.0138)	(0.00608)	(0.00163)
Day of Football	0.00882	-0.0530***	-0.0120**	-0.00972***
	(0.0102)	(0.00972)	(0.00553)	(0.00156)
1 Day After	-0.00282	-0.0839***	-0.0145***	-0.00249*
	(0.00831)	(0.0108)	(0.00518)	(0.00144)
2 Days After	-0.0119	-0.0697***	-0.00637	-0.00326*
	(0.00996)	(0.0139)	(0.00520)	(0.00169)
3 Days After	-0.0212*	-0.0795***	0.0224***	0.00678***
	(0.0124)	(0.0247)	(0.00662)	(0.00211)
4 Days After	-0.0190*	-0.111***	-0.0128**	-0.00910***
	(0.0103)	(0.0161)	(0.00598)	(0.00199)
log(Active Subscribers)	1.397***			
	(0.0281)			
log(All Calls)		1.200***		
		(0.147)		
log(In-Nwk Calls)			-0.192***	0.126***
			(0.00320)	(0.00162)
_cons	-0.453**	-3.624**	6.080***	-0.262***
	(0.180)	(1.409)	(0.0265)	(0.0139)
N	28473	94227	94227	94227

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Violence vs. national events

	(1) log(All Calls)	(2) log(Active Subscribers)	(3) log(In-Nwk Calls)	(4) log(Call Duration)	(5) log(All Calls)	(6) log(In-Nwk Calls)
4 Days Before	-0.156***	-0.0754***	-0.229***	-0.00811***	-0.0412***	-0.0468***
	(0.0100)	(0.00646)	(0.00428)	(0.00222)	(0.00253)	(0.0168)
3 Days Before	0.0212*	0.0353***	-0.00372	-0.0206***	-0.0352***	-0.0224***
	(0.0121)	(0.00898)	(0.00668)	(0.00303)	(0.00194)	(0.00453)
2 Days Before	-0.271***	-0.189***	-0.267***	0.0611***	0.0130**	0.0408
	(0.0129)	(0.00855)	(0.00772)	(0.00245)	(0.00531)	(0.0306)
1 Day Before	0.363***	0.204***	0.358***	-0.0348***	0.0696***	-0.0813**
	(0.0150)	(0.0116)	(0.0109)	(0.00446)	(0.00518)	(0.0379)
Day of Festival	0.414***	0.264***	0.464***	-0.0315***	0.0217***	-0.00605
	(0.0167)	(0.0132)	(0.00875)	(0.00459)	(0.00654)	(0.0416)
1 Day After	0.373***	0.247***	0.449***	-0.0601***	0.0109*	0.0153
	(0.0139)	(0.0110)	(0.00665)	(0.00382)	(0.00659)	(0.0387)
2 Days After	0.413***	0.282***	0.501***	-0.100***	-0.00566	0.0307
	(0.0118)	(0.00926)	(0.00660)	(0.00388)	(0.00747)	(0.0421)
3 Days After	0.433***	0.271***	0.483***	-0.0907***	0.0302***	-0.00273
	(0.0187)	(0.0141)	(0.0107)	(0.00524)	(0.00691)	(0.0430)
4 Days After	0.546***	0.264***	0.581***	-0.0821***	0.166***	-0.0459
	(0.0202)	(0.0142)	(0.00846)	(0.00465)	(0.00662)	(0.0559)
log(Active Subscribers)					1.478***	
					(0.0254)	
log(All Cals)						1.192***
						(0.106)
Observations	28473	28473	94227	94227	94227	94227

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Varying the distance to violence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		log(In-Nwk Calls)				log(Active Subscribers)		
	0.25°	0.50°	0.75°	1.00°	0.25°	0.50°	0.75°	1.00°
4 Days Before	0.0257	0.147***	0.124***	0.0684***	0.0267	0.0769**	0.0654***	0.0590***
	(0.0927)	(0.0428)	(0.0318)	(0.0253)	(0.0323)	(0.0346)	(0.0202)	(0.0191)
3 Days Before	0.0311	0.150***	0.108***	0.0390	0.0249	0.0647**	0.0577***	0.0504***
	(0.0944)	(0.0441)	(0.0330)	(0.0255)	(0.0273)	(0.0255)	(0.0206)	(0.0184)
2 Days Before	0.0744	0.192***	0.156***	0.104***	0.0791	0.0717**	0.0576***	0.0500**
	(0.100)	(0.0497)	(0.0362)	(0.0283)	(0.0611)	(0.0341)	(0.0217)	(0.0203)
1 Day Before	0.0931	0.145***	0.144***	0.121***	0.0178	0.0307	0.0536**	0.0285
	(0.0614)	(0.0392)	(0.0283)	(0.0246)	(0.0259)	(0.0209)	(0.0224)	(0.0197)
Day of Violence	0.171***	0.256***	0.257***	0.199***	0.0170	0.0926***	0.115***	0.0794**
	(0.0605)	(0.0388)	(0.0310)	(0.0309)	(0.0278)	(0.0315)	(0.0296)	(0.0313)
1 Day After	0.00844	0.105***	0.104***	0.0642**	0.0426	0.0717**	0.0625**	0.0365
	(0.0622)	(0.0382)	(0.0292)	(0.0283)	(0.0304)	(0.0295)	(0.0294)	(0.0286)
2 Days After	0.00856	0.0718*	0.0655**	0.0823***	-0.000962	-0.00931	0.0214	0.0284
	(0.0637)	(0.0410)	(0.0299)	(0.0265)	(0.0211)	(0.0347)	(0.0264)	(0.0234)
3 Days After	-0.0438	0.0417	0.0510*	0.0656***	-0.00391	0.0145	0.0187	0.00433
	(0.0637)	(0.0359)	(0.0264)	(0.0235)	(0.0300)	(0.0259)	(0.0232)	(0.0189)
4 Days After	0.0288	0.0916**	0.0783***	0.0733***	0.0335	0.0762**	0.0353*	0.0269
	(0.0625)	(0.0359)	(0.0264)	(0.0241)	(0.0316)	(0.0343)	(0.0202)	(0.0180)
N	94227	94227	94227	94227	28473	28473	28473	28473

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Varying the definition of violence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(In-Nwk Calls)				log(Active Subscribers)			
	All	Fatal Only	Including date Uncertain	Fatal With Certain Date	All	Fatal Only	Including date Uncertain	Fatal With Certain Date
4 Days Before	0.0556^{**}	0.147^{***}	0.0930^{***}	0.449^{***}	0.0374^{*}	0.0769^{**}	0.0417^{***}	0.185^{**}
	(0.0249)	(0.0428)	(0.0291)	(0.0250)	(0.0197)	(0.0346)	(0.0156)	(0.0750)
3 Days Before	0.0363	0.150^{***}	0.116^{***}	0.478^{***}	0.0345^{**}	0.0647^{**}	0.0694^{***}	0.186^{***}
	(0.0226)	(0.0441)	(0.0278)	(0.0233)	(0.0147)	(0.0255)	(0.0167)	(0.0680)
2 Days Before	0.0668^{***}	0.192^{***}	0.214^{***}	0.725^{***}	0.0490^{**}	0.0717^{**}	0.0700^{***}	0.225^{***}
	(0.0239)	(0.0497)	(0.0320)	(0.0306)	(0.0206)	(0.0341)	(0.0217)	(0.0730)
1 Day Before	0.0440^{**}	0.145^{***}	0.247^{***}	0.806^{***}	0.0142	0.0307	0.0407^{**}	0.182^{**}
	(0.0214)	(0.0392)	(0.0327)	(0.0393)	(0.0118)	(0.0209)	(0.0167)	(0.0794)
Day of Violence	0.157^{***}	0.256^{***}	0.314^{***}	0.874^{***}	0.0587^{***}	0.0926^{***}	0.0715^{***}	0.183^{***}
	(0.0224)	(0.0388)	(0.0380)	(0.0426)	(0.0177)	(0.0315)	(0.0192)	(0.0696)
1 Day After	0.0715^{***}	0.105^{***}	0.170^{***}	0.434^{***}	0.0376^{**}	0.0717^{**}	0.0537^{**}	0.155^{*}
	(0.0229)	(0.0382)	(0.0404)	(0.0904)	(0.0153)	(0.0295)	(0.0220)	(0.0937)
2 Days After	-0.0570^{*}	0.0718^{*}	-0.0386	0.441^{***}	-0.0615^{***}	-0.00931	-0.0758^{**}	0.0645
	(0.0302)	(0.0410)	(0.0553)	(0.0946)	(0.0231)	(0.0347)	(0.0362)	(0.0947)
3 Days After	0.00187	0.0417	-0.0353	0.352^{***}	-0.0338^{**}	0.0145	-0.0689^{***}	0.0336
	(0.0307)	(0.0359)	(0.0396)	(0.0866)	(0.0168)	(0.0259)	(0.0267)	(0.0887)
4 Days After	0.251^{***}	0.0916^{**}	0.265^{***}	0.377^{***}	0.129^{***}	0.0762^{**}	0.189^{***}	0.138
	(0.0355)	(0.0359)	(0.0452)	(0.0876)	(0.0270)	(0.0343)	(0.0481)	(0.0890)
N	94227	94227	94227	94227	28473	28473	28473	28473

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$