How Do Firms Respond to Insecurity? Evidence from Afghan Corporate Phone Records*

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Abstract

We provide new evidence on how insecurity affects firm behavior by linking data on violent conflict in Afghanistan to geo-stamped corporate mobile phone records. We begin by developing a method for observing firm location choice with phone data, and validate these measurements using independent sources of administrative and survey data. Next, we show that deadly terrorist attacks reduce the presence of firms in affected districts by 4-6%. The effect is driven by both an increase in the local exit of existing firms following attacks and a decrease in new firm entry. We find large negative spillovers from attacks in provincial capitals on firm presence in nearby rural districts. After violence, employees in provincial capitals are 33% more likely to move to Kabul and 15% more likely to leave for another province, with strongest effects when employees experience violence outside of their firm's primary district of operation.

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1 Introduction

A vibrant private sector is central to long-run growth, motivating a long-standing interest in understanding the institutional barriers to private sector development (North, 1990; Svensson, 1998). This literature has documented important barriers to firm growth, such as regulatory quality, capital constraints, and rule of law (Hallward-Driemeier and Pritchett, 2015). However, while one-fifth of the world's population now lives in insecure countries, there is much less research on how firms respond to insecurity (Baranyi et al., 2011). Part of this knowledge gap stems from a scarcity of data on firms during and after violent conflict (Besley and Mueller, 2018).

This paper makes methodological and substantive contributions to understanding private sector responses to insecurity by studying how firms behave during a period of violent conflict in Afghanistan.[1] Methodologically, we develop and validate a new approach for measuring the presence, entry, and exit of private firms at high frequency and spatial granularity. These measures are based on administrative records of corporate mobile phone activity, which we obtain from a large mobile phone operator in Afghanistan, and which contain over 200 million corporate phone call records across 173 districts between 2013-2016. We validate these novel measurements of firm behavior with five independent data sources, including administrative data from the Afghan government, World Bank survey micro-data, nightlights data, and an original survey we conducted with 454 companies that appear in our call record data.

We then use these measures to better understand how the private sector responds to terrorist attacks in Afghanistan. As intuition, Figure 1 shows how private firms responded to the Taliban's violent seizure of Kunduz, the country's fifth largest city, in September 2015.

[1]Since 2001, Afghanistan has received substantial foreign assistance including for private sector development. USAID, for example, provided \$1.2 billion for economic growth projects and \$2.1 billion for agriculture programs between 2002-2017. In addition, the U.S. Department of Defense spent \$675 million on private sector development through its Task Force on Business and Stability Operations. According to one U.S. Government study, "U.S. officials viewed private sector development as foundational to economic growth, which in turn was seen as a key driver of security." (SIGAR 2018 viii). The same study reported that America's understanding of Afghanistan's private sector was limited; "investment in Afghanistan," it said, "is difficult due to the lack of precise numbers and other gaps in information." (SIGAR 2018, 11).

There was an immediate and pronounced drop in firm presence after insurgents took over the city. The reduction, driven by the relocation of corporate subscribers beyond the city limits, persisted into the following month when Afghan forces cleared the city, and remained permanently depressed, even after the government forces regained control of the city.

Our main results generalize from this single event to the countrywide effects of all major terrorist attacks that occur during the four-years for which we have mobile phone records. We focus on attacks in the top percentile of confirmed fatalities (district-months with greater than 20 deaths), as recorded by the Global Terrorism Database. Our primary empirical approach uses panel fixed-effects regressions to estimate the effect of terrorism on the location choices of 2,306 firms. While violence is not randomly assigned, and the attacks we study may be correlated with underlying changes in the local economic and security environment, our preferred specification, which includes both firm-by-district and month fixed effects, as well as linear and quadratic district-specific time trends, seeks to isolate changes in firm behavior caused by unanticipated increases in local violence. We highlight four main results.

First, we find that firms respond to large terrorist attacks by immediately reducing their presence in affected districts by 4-6%. Our measurement strategy also makes it possible to decompose the reduction in private sector activity into different firm-level decisions. The overall effect is driven both by an increase in firm exit and a decrease in firm entry. Firms are 8-16% less likely to enter a district that experienced a terrorist attack and 6-23% more likely to exit. The effect is most pronounced in the first month, with modest evidence of persistence in subsequent months.

Next, we show evidence of spatial heterogeneity and spillovers to other districts. Firm response to terrorism is strongest following events in provincial capitals. Attacks in provincial capitals also lead to reductions in firm presence in surrounding rural districts — an effect nearly half as large as the direct impact of attacks on rural districts themselves.

Third, disaggregating the data from firms to individuals, we find that individual employees are more likely to move after being exposed to terrorist attacks. Attacks in provincial capitals, excluding Kabul, lead to a 33% increase in movement to Kabul and a 15% increase in movement to another province. However, employee response depends on geography. While employees exposed to terrorist attacks in their firm's primary district of operations are no more likely to change locations, employees outside that district increase the likelihood of leaving that location by 32% following a terrorist attack.

Finally, we find suggestive evidence of heterogeneity in response to insecurity by firm size. Our results on firm level presence, entry, and exit are concentrated among larger firms — where firm size is proxied by the total number of phone numbers assigned to a corporate account. These effects are greater for larger firms than for smaller firms, in both absolute and relative (to the mean) size. In the disaggregated data, it is similarly the employees of large firms who are induced to move after violence (with no detectable effect for employees of smaller firms). These findings are consistent with previous research that finds larger firms appear to be more susceptible to predation and devote more resources to security (Besley and Mueller, 2018). However, these results are also consistent with larger firms having greater capacity to relocate in response to violence.

Taken together, these results paint a nuanced picture of how firms respond to insecurity. A key feature defining insecure environments is uncertainty and downside risk. Violent conflict has the potential to disrupt economic activity, exposing business assets to potential loss and damage while personnel risk possible injury or death. Firms in these contexts must therefore make difficult choices about where to operate based on their perceptions of the current security environment and expectations of future insecurity. We show that firm activity is indeed substantially impacted by terrorist attacks, with immediate and significant effects on firm entry and firm exit. While we find only modest evidence of persistence beyond the first month, as with natural disasters, short-lived impacts on firm location choice are likely to disrupt productive activity, impeding deliveries, delaying meetings, and distorting investments (Botzen et al., 2019).

Our work engages a burgeoning literature on the economic consequences of insecurity.[2] Important examples have highlighted the macroeconomic consequences of violent conflict on GDP in Spain (Abadie and Gardeazabal, 2003), on long-run growth in Vietnam (Miguel and Roland, 2011), on investment in Israel (Fielding, 2004), and on housing prices in Ireland (Besley and Mueller, 2012). By exploring heterogeneous firm responses in urban areas, our work also contributes to a literature on agglomeration by highlighting the importance of security as an amenity in cities (Glaeser, 2010; Puga, 2010). In a developed world setting, Brodeur (2018) finds that terrorist attacks decrease employment in targeted U.S. counties.

However, studying firm response to insecurity in developing countries *during* an active conflict presents major challenges, where lack of security directly contributes to a paucity of data suitable for that purpose. To our knowledge, this is the first concerted effort to measure the behavior of private firms in developing countries using passively-collected digital data.[3] With a few notable exceptions, studies that demonstrate the microeconomic mechanisms underlying the aggregate relationship between conflict and economic activity are limited. Guidolin and La Ferrara (2007) show how conflict impacts the public valuation of Angolan diamond companies. Ksoll et al. (2016) show the effect of electoral violence on labor supply in Kenya. Amodio and Di Maio (2017) show how conflict affects firms' upstream access to inputs. We also complement recent work by Besley and Mueller (2018), who use World Bank survey data on the costs of protection for firms in predatory environments. We contribute to this literature by documenting micro-level firm behavior in conflict settings, introducing a novel measurement approach of firm activity, and demonstrating adjustments to firm location choices in response to terrorist attacks.[4]

[2] See Collier et al. (2003) and Blattman and Miguel (2010) for overviews of research linking aggregate economic activity and insecurity.

[3] This methodology extends work by Blumenstock et al. (2015), who use mobile phone data to analyze the distribution of wealth and poverty in Rwanda, as well as recent work using satellite imagery to measure productivity and wealth (Henderson et al., 2012; Jean et al., 2016). Prior work does not typically differentiate private firms from other types of mobile phone activity.

[4] Ciarli et al. (2015) find higher rates of self-employment in conflict-affected areas of Afghanistan using household survey data, and our results imply formal employment opportunities may fall with insecurity.

2 Economy and Security in Afghanistan

2.1 Insecurity in Afghanistan

The World Bank characterizes Afghanistan as a “deeply fragile and conflict-affected state” (World Bank, 2016). Afghanistan’s history has been marred by conflict and political instability for decades since the Soviet Union invaded the country in 1979. In 1996, the Taliban, an Islamic fundamentalist political movement with backing from Pakistan, took control of the country. The United States invaded Afghanistan following the September 11, 2001 attacks by al-Qaeda and the Taliban’s refusal to turn over al-Qaeda’s leader, Osama bin Laden.

While prospects for security appeared to improve at the beginning of the U.S. intervention, by 2006 the Taliban insurgency reemerged, mounting a series of increasingly violent attacks from Pakistan with financial and technical support from its intelligence services. In response, the United States, with NATO support, launched a surge of troops in 2009, again pushing the Taliban to the most remote parts of the country and across the border back into Pakistan. That time, just before the period of this study, was one of relative calm and security. However, “the surge” was linked to a transition plan to draw down U.S. forces starting in 2012 and a handover of responsibility for security operations to the Afghan National Security Forces by 2014. In December 2014, NATO forces formally ended combat operations in Afghanistan, though international troops continued to serve as advisors.

The transition to Afghan leadership in the counter-insurgency campaign was associated with a sharp escalation in the level, trend and geographic scope of insecurity across the country. As Figure 2 shows, the five years from 2012-2016, covering the period of this study, marked a steady increase in the number of confirmed fatalities from terrorist attacks, with over 8500 civilians killed in 2016, and a corresponding increase in the number of Afghan districts perceived as insecure. That this rising violence takes place after a period of relative stability and sustained growth motivates our interest in firm responses to violence in a period of increasing insecurity.

2.2 Afghanistan's Economy

With nominal GDP per capita under 600 USD, Afghanistan is among the poorest countries in the world. For a decade after the Taliban's fall in 2002, growth averaged 9.4 percent per annum, but this "rapid and volatile" growth, owing to an influx of development assistance, changes in agricultural prices, and military spending, did not translate into a durable reduction in poverty (World Bank, 2015). Poverty levels did fall in regions that saw the most intense fighting, but this was largely due to economic spillovers from military spending (Floreani et al., 2016). With the drawdown of international forces starting in 2012, corresponding decreases in development aid, and increases in the intensity of conflict, Afghanistan entered a recession and poverty levels again began to rise.

Despite this troubling context, considerable economic activity persists throughout the country. From a sectoral perspective, the UN Food and Agriculture Organization estimates that agriculture constitutes 25 percent of GDP and 58 percent of employment, with the remainder divided between industry and services. In 2009, the Integrated Business Environment Survey (IBES) estimated approximately 400,000 firms operating in Afghanistan. 94% of these firms are small, containing less than nine employees. Firms with over 500 employees comprise just .17% of all firms, but support nearly one-third of all industrial employment. SMEs, with 10-499 employees, contribute the least to national employment.

However, mirroring global trends, Afghanistan is becoming more urban, with economic agglomeration appearing in capital cities, chiefly Kabul. According to the World Bank, Kabul's "population grew by a staggering 4.5 percent a year between 2010 (3.72 million population) and 2015 (4.64 million population). Urbanization was largely informal, with an estimated 73 percent of the population living in unplanned areas. These unplanned areas not only make services provision hard, but have also started to encroach on valuable agricultural land on the peripheries." (Ellis and Roberts, 2015, p. 110). Our data will also show that, when faced with violence, firms move to Kabul or other provincial capitals, which provide the markets, labor and security they seek.

While the majority of employment in Afghanistan is informal, there is significant formal sector activity that continues despite conflict, weak institutions and limited infrastructure. And yet, beyond these coarse tallies, there is very little existing data on investment and the private sector in Afghanistan (World Bank, 2015).[5] Such formal firms represent key drivers of long-run economic growth and job creation (Klapper and Richmond, 2011) and are the focus of this paper.

2.3 Firms & Insecurity in Afghanistan

To learn more about how important insecurity is among the challenges facing Afghan firms, we conducted a survey of 454 business owners from our full sample of firms in the mobile phone record data (discussed further in the next section). 82% of firms reported that they viewed security as the primary obstacle to their businesses. In listing all challenges facing their businesses, 91% included security, while power cuts (85%), labor problems (80%), and infrastructure (74%) were the next three highest responses, all plausibly linked to issues of security.[6] Further underlining the preeminence of security, one Afghan business owner explained that he needed security to feel safe to complain about the other issues.[7]

Focus group discussions gave further insights into the broad range of issues encapsulated in insecurity, with different respondents emphasizing road security while transporting goods, corruption of customs officials, and simple street harassment and gender-linked violence all cited by participants.[8] Insecurity resulting from anti-government groups remains the primary concern of firms as 78% said they were very affected by insecurity from anti-government groups generally, and even more said they were concerned about land mines or IEDs (84%), small arms fire (83%), kidnappings (82%), and suicide bombers (93%) specifically.[9]

[5] See Ghiasy et al. (2015) for a recent overview of the private sector in Afghanistan.

[6] In the 2014 World Bank Enterprise Survey in Afghanistan, the most commonly cited obstacle to business was "political instability"; other top answers included "corruption and crime" and "theft and disorder" (World Bank, n.d.)

[7] Anonymous. 2015. Interview with construction firm executive by author. March

[8] Anonymous. 2015. Focus group of business owners with author. March.

[9] We explore the representativeness of our survey sample in Appendix Table A1.

3 Data

Our primary data source comes from an administrative data set of 200 million corporate call records. We combine this with a range of complementary data sources including administrative government records, World Bank survey micro-data, satellite nightlights data, and original firm survey data to achieve a fine-grained perspective on the economic behavior of private firms in Afghanistan during a period of increasing insecurity.

Since 2002, mobile phone penetration in Afghanistan has grown rapidly, with four private and one public operator serving over 19.7 million subscribers out of an estimated population of 21.5 million adults (World Bank 2015). We document firms' locations over time using anonymized call detail records (CDR) of corporate accounts from one of Afghanistan's largest mobile network operators. Corporate account holders were comprised of registered businesses who had signed up for a corporate pricing plan that allowed for the linking of multiple phones to a single corporate account.[10] We observe the corporate account names of these organizational customers as well as the mobile operator's classification of each customer business type (e.g., "construction", "government", "transport", etc) and remove public or non-profit organizations, including health, education and media groups. We remain with a sample of 2,306 private firms with over 125,000 associated subscribers (unique phone numbers) active during our 45 months of data from April 2013 to December 2016.

Firms with corporate phone accounts are likely to be different from other Afghan firms. While we would like to be able characterize this selection of firms relative to all others, a reliable firm census at or near our study period does not exist.[11] An alternative benchmark is the World Bank's Enterprise Survey conducted May-July 2013, which used a stratified random sample of 416 firms re-weighted based on firm size, sector, and location strata. In

[10] Such calling plans typically allow consolidated billing services or discounts for within-organization calls.

[11] The Central Statistics Office completed an Integrated Business Enterprise Survey (IBES) in 2009, which included a screening survey that attempted a census of every firm with 10 or more employees in the country and used random area sampling for firms with fewer than 10 employees. Some administrative data sets do exist for this period, but each have their own limitations. For example, official business registration databases simultaneously under-count firms that do not register to evade tax obligations and over-count the registration of "ghost" firms created to pursue contracts.

Table A1, we show that, on average, the firms in our CDR data appear to have twice as many subscribers as the number of employees from firms in the Enterprise Survey sample, that the CDR firms are less likely to appear in trade or manufacturing categories, and that CDR firms are more likely to have their headquarters based in Kabul. Although there is still considerable overlap, our sample of firms is not representative of all firms in Afghanistan. Our sample is comprised of relatively large formal firms, a group that accounts for a major portion of formal employment and that is, therefore, of particular interest as potential drivers of economic growth.

3.1 Measuring Firm Presence and Movement

We use the CDR data to measure firm presence and movements over time. This data contains a record of each call, anonymized identification numbers for the calling and called parties, the date and time of the call, and the coordinates of the cell phone tower of the calling party. We do not observe any content of their communication. These data reference 1,350 active cell phone towers distributed across 267 of Afghanistan's 398 districts, which collectively cover over 80% of the population.[12]

Table 1 shows wide coverage and considerable variation in the CDR data. Among the 2,306 firms in our data, Panel A shows that the average (median) firm is active for 34 (45) months out of 45 total months of data, by making at least one call in a given month. They are observed in 34 (22) districts throughout the study period and an average of 8.6 (3) districts per month. While the average firm has 52 subscribers, the median firm has only four, indicative of a rightward skewed distribution of firm size. Using the first six months of CDR data for each firm, we identify each firm's "primary" (modal) location and find that 60% appear based in Kabul, 31% in provincial capitals, and another 9% in rural districts.[13]

[12] Afghanistan's challenging terrain, limited infrastructure and persistent insecurity limit the expansion of mobile network coverage to more remote and underpopulated districts.

[13] As discussed below, we compute the top modal district for each firm by calculating the most commonly used district in all outgoing calls for each subscriber in each months, and then recording the frequency that each district appears for each firm.

Going down a level to the 115,520 individual subscribers, Panel B shows considerable variation as well. After initial activation, subscribers are active (make at least one call) in 50% (43%) of months, show 2.3 (2) different districts as their primary location over the period of the study, and switch their primary district location in 8% of months.

Our geographic and temporal units of observation are districts and months. Monthly aggregates ensure that any detected effects are more than fleeting responses to violence. A month delay in a business meeting, delivery, or transaction is likely an economically meaningful distortion for most firms. Due to concern that terrorist attacks could affect cell tower coverage itself, and outages would systematically under count firm presence, we drop districts that have any months with less than 28 days of cell tower coverage over the period of the study. This removes 94 districts (roughly one third of the sample), resulting in 7,785 district-month pairs.[14] Panel C shows that an average (median) district-month has 101 (57) active firms and 507 (149) active subscribers.

Our violence data comes from the Global Terrorism Database (GTD) which contains records of over 10,000 confirmed fatalities from terrorism in Afghanistan.[15] The mean (median) district-month records 1.3 (0) GTD killings, with a maximum value of 244 killings.[16] We define major violent events as district-months with the top 1% of killings in insurgent-linked attacks, equal to having had at least twenty confirmed fatalities. Killings constitute are more objective measure of conflict intensity than others where attacks, threats, or documented damages are more prone to reporting distortions or biases. The 1% threshold is somewhat arbitrarily chosen, however, given the magnitude and source of the data, from

[14]Our results are stronger when including these dropped districts. We also confirm that our results are robust to dropping only district-months with less than 28 days of coverage, instead of the entire district.

[15]Maintained by National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland, the GTD database is constructed from keyword filtering of high-quality media sources and hand coded by teams of researchers, including providing geo-coordinates for the city or district an event takes place. Killings include confirmed fatalities of either victims or attackers. Thus, in order to be included in our dataset, a killing must be recorded by a credible media source and meet the GTD coding team's definition of terrorism: "the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation." While this may lead to under-measuring incidents, it increases our confidence that we are focused on meaningful events.

[16]This observation corresponds to the attack on Kunduz in September 2015 discussed in Appendix C1.

media coverage within Afghanistan, we can be confident that these major events are salient to people within Afghanistan, and are likely to result in updating of peoples' perceptions of security in the affected areas. We show robustness of our analyses to the choice of other thresholds and definitions of major events in the appendices.

Finally, Panel D shows variation in firm presence and movement at the firm-district-month level, the data structure used for our first results below.[17] Our primary coding of firm presence emphasizes the extensive margin indicating that any subscriber associated with the firm made any calls from a district in a given month. Firm presence in a given district-month is 5% on average across all firms. We also employ a more restrictive measure where firm presence requires that a given district was the primary (modal) calling location for one of the subscribers linked to their firm in that month. This more restrictive measure shows that firms were "modal" present in a given district-month 1.7% of the time across all firms.

3.2 Data Limitations

Call Detail Records (CDR) provide an objective account of the locations from which individual employees make and receive phone calls. Such data offer several advantages over traditional survey-based approaches to tracking firm location choices. Indeed, it is difficult to imagine collecting detailed information on the time, duration, and location of the movements of their employees over a four year period through direct questioning of a firm representative. By contrast, the phone data are sufficiently granular in space and time to enable new identification strategies, including the panel fixed effects regressions that we use. However, there are also limitations to these data worth recognizing.

CDR provide highly credible, affirmative identification of times and locations. We expect that the data contain a very low incidence of type 1 (false positive) errors. However, when phones are off or simply not being used for outgoing calls, location cannot be measured. As noted in the previous section, many subscribers go "off" for stretches of time, leaving us

[17] A brief description of the data processing required to complete this task is included in Appendix A1.

unable to ascribe a location during that period. The data are therefore susceptible to type 2 errors (false negatives).

Second, within a firm, *who* is given a linked mobile phone is unknown. Therefore, the footprint of the firm, as captured by the presence of employees, may not be the firm's entire footprint. If firms preserve linked phones for more senior employees, this may therefore reflect a higher level of firm investment and economic signal than the average employee. In part to address this uncertainty of within firm selection, our analysis uses firm fixed effects throughout, accounting for time-invariant differences in mobile phone usage by firm.

A final concern is that phone usage itself is likely to be impacted by insecurity. In particular, firms in our survey reported that they were more likely to make calls and to check in more frequently with others when entering into dangerous areas. We explore some of these responses in the analysis that follows, in particular by focusing on variation in whether or not employees make any calls in months following exposure to violence. This has two main implications for interpreting the results that follow. First, if firms are more likely to make calls when operating in insecure areas, reductions in firm presence measured after major violent events are likely to be an underestimate of the actual affects of the episode. And conversely, positive effects may be capturing increases in phone usage in addition to actual shifts in firm presence. We return to these points below.

3.3 Measurement Validation

While we view our measures, first and foremost, as objective indicators of firm presence, it is also worth contrasting our measures with other data sources. In Figure 3, we conduct a principal component analysis of the three main sources of variation in our district-month panel (the logs of active firms, active subscribers and calls) and plot the first principal component for April 2013 on a map of Afghanistan's districts. As expected, major urban centers such as Kabul (center-north), Kandahar (south), Hirat (west), Mazar (north-west), Kunduz (north-west) and Jalalabad (east) are clearly visible. For reference, red dots in the figure mark locations of GTD recorded killings from May 2012-April 2013, demonstrating the nationwide geographic distribution of violence that we exploit in the analysis.

Next, we validate the physical location of firms against CDR measures in Table A2. For each firm appearing in the CDR, we compute the top one and five "modal districts". This is done by calculating the most commonly used district in all outgoing calls for each subscriber in each month, and then recording the frequency that each district appears for each firm.[18] In Panel A, we compare these modal districts to the headquarter district locations from two official business registration sources collected in 2016 as well as a set of 414 firms interviewed in our own, original survey conducted in 2017. The Central Business Registry (CBR) is where formal firms must register to receive a tax identification number and the Afghanistan Investment Support Agency (AISA) is a database of firms seeking foreign investment. We successfully name match 934 firms to the CBR dataset and 110 firms to the AISA dataset. Across these three data sources, our top modal, or "primary", district identified in the CDR matches their reported headquarters between 73 and 83% of the time. Their reported headquarters is included in the CDR's top 5 modal districts between 83 and 93% of the time.[19] These findings increase our confidence in the potential of CDR data to proxy for employees' physical locations.

Next, we compare records of firm size with measures from our CDR data in Table A3. Using the CDR data, we calculate the number of subscribers (unique phone numbers) active from January-March 2014, winsorizing the top 1% to mitigate the influence of outliers. We then compare these subscriber totals to reported firm employment numbers gathered during April and May 2014 as part of the screening survey for the Central Statistics Office's Integrated Business Enterprise Survey (IBES). We successfully name match 190 firms in both data sets and find a robust, positive relationship between these two independent measures of

[18] Note that the number of modal districts for a firm is bounded by the number of subscribers. The average (median) firm has 5.8 (2) modal districts.

[19] We complete a second validation exercise using our survey data in Panel B where firms reported districts of headquarters and other offices in 2014 and 2017. We find that 67% of 2017 office districts match the top five modal districts and that 70% match the top ten modal districts, with similar percentages in 2014.

firm size with a cross-sectional correlation of .79 in levels in column (1) of Panel A ($p < .05$) and .22 in logs in column (1) of Panel B ($p < .01$).[20] We repeat this exercise again, comparing the number of unique CDR subscribers in October-December 2019 with our original survey data from spring 2017, and retrospectively reported employee numbers from three years earlier in October-December 2013. We find a strong cross-sectional correlation between self-reported employees in 2017 of .57 in levels ($p < .05$) and .23 in logs ($p < .01$). Although we acknowledge that different firms are likely to use their corporate lines differently, some maintaining extra lines and others only assigning lines to select employees, these results suggest that active subscribers can provide useful information about firm size.[21]

Overall, these validation exercises increase our confidence in the economic content of the CDR data. Firm location and firm size are all correlated with CDR based measures, with the validation of firm location measures particularly robust. Limitations notwithstanding, this suggests the potential of this methodological approach, particularly in conflict-affected settings like Afghanistan where reliable temporal or spatial data on firm activity is scarce.

4 How Do Firms Respond to Insecurity?

4.1 Firm Level Location Choices

We begin our analysis of the impact of terrorist attacks on firm location choices with a firm-district-month panel. As discussed in Section 3.1, we use the CDR data to determine in which districts the firm was present in each month following two definitions: that any subscriber linked to the firm's account made any calls from that location, or that the district was the modal calling location for one of the firm's subscribers in that month. Our primary

[20] The IBES survey sample combined a listing of 4,000 establishments with 10 or more employees (including public and non-profit organizations) and a random area sample of establishments with less than 10 employees.

[21] In Appendix Figure A1, we demonstrate this particular concern holds for single-subscriber firms, which share a similar size distribution of self-reported employees as firms with more than one subscriber. In columns (5)-(8) of Table A3, we show the correlations between number of employees and number of subscribers are consistently larger after dropping single-subscriber firms.

independent variable is an indicator, Major Terrorist Attack (MTA), for a district-month being in the top 1% of recorded fatalities in insurgent-linked attacks, a threshold equivalent to greater than 20 killings.[22]

We estimate the relationship between firm presence and these terrorist attacks using the following preferred estimating equation:

$$Y_{idt} = \beta \mathbb{1}(MTA)_{dt-1} + \theta_{id} + \delta_t + \sigma_{dm} + \gamma_d * t + \mu_d * t^2 + \epsilon_{idt} \tag{1}$$

where Y_{idt} is an indicator variable that equals 1 if firm, i, is present in district, d, in month t. $\mathbb{1}(MTA)_{dt-1}$ is the indicator variable for 21 or more killings in district d in month $t-1$, $\theta_{i,d}$ is a set of firm-district fixed effects controlling for a firm's average presence in a given district. δ_t are month fixed effects while σ_{dm} are a set of district-calendar month fixed effects that capture seasonal variation in violence and firm activity. $\gamma_d * t$ and $\mu_d * t^2$ are district-specific linear and quadratic time trends. Throughout, we cluster our standard errors, ϵ_{idt}, at the district-level. Our coefficient of interest is β, which we interpret as the average treatment effect of terrorist attacks on firm presence. To support a causal interpretation, the required identifying assumption would be that killings are independent of economic factors after conditioning on θ_{id}, δ_t, σ_{dm}, $\gamma_d * t$ and $\mu_d * t^2$. While violence is not randomly allocated, and the attacks we study may be correlated with underlying changes in the local economic and security environment, this specification isolates the discrete change in firm behavior after major unanticipated events.

Local Response to Terrorist Attacks

Table 2 presents the main results on the impact of terrorist attacks on firm presence in the affected district. Panel A uses the first outcome measure of any subscriber activity

[22] 17% of district-months have at least one insurgent-linked death recorded, so this threshold is approximately equivalent to the top 6% of terrorist attacks that result in any deaths. After dropping districts without complete CDR coverage, we count 70 such attacks distributed across 38 districts across the country and appearing in 37 of our 45 months of data.

and Panel B uses the second measure of modal subscriber activity. Column (1) shows the raw correlation without fixed effects. It is positive but noisily estimated. This correlation likely reflects that terrorist attacks often take place near urban centers with more economic activity. In column (2) we include district-by-firm fixed effects to control for time-invariant district characteristics as well as each firm's propensity to be there. Including these fixed effects flips the sign of the correlation and gains statistical significance. Column (3) adds month fixed effects to control for unobserved time-varying factors affecting violence and firm activity across the country, and in column (4) we add district-by-calendar month fixed effects to address district-specific seasonality such as fighting or migration patterns. Finally, columns (5) and (6) add linear and then quadratic district specific trends to isolate discrete changes in firm presence following major terrorist attacks.

The magnitude of our estimated coefficient in column (4) of Panel A implies that major terrorist attacks are associated with a 20 percent reduction ($p < .05$) in the likelihood of firm presence in the following month (reported as "Beta/Mean"). Violence, however, is not randomly allocated, and if we preferred to consider these major events as markers of local security, then these estimates, without district trends, would capture the broader shifts in firm presence associated with deterioriating security. Instead, we prioritize a narrower focus, on the discrete updates and adjustments resulting from these unexpected events as estimated with inclusion of the district linear and quadratic trends, in column (6). As expected, the estimated effect attenuates after including these trends – falling to 4 percent in column (6) of Panel A – but remain significant at the 1% level. We use this as the preferred specification for the remainder of this section.

In Panel B of Table 2, the dependent variable is modal firm activity - assigning each subscriber to only one district for each month based on their most frequent calling location - and we find qualitatively similar patterns to those in Panel A, though the relative magnitude of the effect sizes is larger given lower mean outcomes.[23,24]

In Table 3, we decompose the variation in firm presence into entry and exit and find both an increase in exit and decrease in entry following major terrorist attacks. Column (1) of Table 3 repeats the coefficient from column (6) of Table 2. Column (2) introduces a new outcome variable, Firm Entry, which is an indicator equal to one if a firm is not present in the previous month and then is present in the current month, with presence defined as having any linked subscriber activity. We observe a nearly 8% decrease ($p < .01$) in firm entry in the month after major terrorist attacks. Column (3) introduces the corresponding outcome variable, Firm Exit, which is equal to one if a firm is present in the preceding month and then absent in the current month; firm exit increases by over 5% ($p < .10$) in the month after major terrorist attacks. Columns (4)-(6) show similar patterns using the modal measure of firm presence, though with larger relative magnitude of effect sizes: a 17% decrease in entry ($p < .10$) and a 23% increase in exit ($p < .10$).[25]

Next, we examine persistence of these effects. In Figure 4, we plot the coefficients from estimation of Equation 1, replacing the single lagged indicator for major terrorist attacks with three leads, a current term, and eight lags of the major attacks variable. The results are shown in regression form in column (1) of Table B5. Responses to major attacks are biggest and concentrated in the first month following major attacks: a 5 percent decrease from the mean level of firm presence ($p < .01$). We see some evidence of persistence beyond the first month where the second lag retains marginal significance ($p < .10$) but falls in magnitude to 3 percent. Longer lags remain negative for at least five months, but continue to regress

[23]Both measures of firm presence have strengths: any subscriber activity picks up on short-term visits that may be business related, while the modal subscriber activity focuses on the most frequent location.

[24]In Appendix Table B3, we show these results are robust to constructing an unbalanced panel that only drops district-month observations with less than 28 days of cell coverage. In Appendix Table B4, we show these results are also robust to restricting the panel to only calls made during the Afghan work week (e.g., 9am-5pm local time, Sunday-Thursday), though the standard errors increase in the modal results in Panel B. In general, we prefer to use the full period of daily calling activity for districts that always have cell coverage and focus attention on comparing the any activity measures to the modal activity measures.

[25]Appendix Table B5 shows relative magnitudes can be 2-5 times larger when dropping district-specific linear and quadratic trends.

back to zero and lose statistical significance.[26]

Spatial Heterogeneity and Spillovers

The effects of terrorist attacks are unlikely to be uniform across all areas. Updating of beliefs about security is likely to depend on the type of area affected and whether it is relatively more remote or urban. Major attacks may impact surrounding areas as well, sending a signal of insecurity that extends beyond district borders. The spatial dimension of our data gives us a unique opportunity to look at regional heterogeneity and province-level spillovers. Column (1) of Table 4 repeats the main result of local response to major attacks, with a .2 percentage point decrease in local firm presence following major attacks. Column (2) shows that, while not statistically distinguishable, the magnitude of effects in capitals is nearly twice as large as in rural areas. Column (3) introduces a province-level indicator for whether any district in the province experienced a major attacks in the previous month. Controlling for local response to violence (the first two terms), we see a positive but insignificant point estimate on the province-level treatment. Standard errors are clustered, more conservatively, at the province level.

However, the estimate in column (3) masks heterogeneity based on whether this event took place in the provincial capital district or in one of the surrounding "rural" districts. Column (5) suggests that there may be positive spillovers in firm presence in response to major attacks in rural areas. Part of this response is likely to be displacement, as firms located or operating in one district shift away to other nearby areas. Columns (6) and (7) split the sample by capital and rural districts, respectively. We see point estimates of similar magnitude, although this response, relative to the mean appears to be bigger in rural

[26] We also note some evidence of anticipation prior to major terrorist attacks. Appendix Table B7 applies the event study specification to Firm Entry and Firm Exit as well as the modal variables from Table 3. While the first and second leads in column (1) have point estimates near and statistically indistinguishable from zero, the third period lead term has a negative coefficient that is 3 percent of the mean value ($p < .10$). In column (3) we see significant increases in firm exit prior to major attacks, suggesting that firms may observe proximate changes in the security environment and seek to exit prior to major attacks. The results using the modal activity measures in columns (4) - (6) are consistent with the "any activity" measures, though we have less statistical power due to the lower base rate of firm presence.

districts. However, as discussed in Section 3.3, the CDR data prevents us from ruling out that increased phone usage in areas of perceived insecurity are also contributing to these estimates and limits our ability to draw strong conclusions.

By contrast, column (4) shows a large and significant negative province wide effect of major attacks in the provincial capitals. This effect is nearly two-thirds the size of the direct effect of locally experienced events in rural areas. Column (8) estimates these two effects simultaneously and finds similar point estimates and statistical significance. The patterns in Panel B, using modal location for employees, are qualitatively similar and more precisely estimated than those in Panel A, with the exception that rural responses to province exposure to terrorist attacks are similar in magnitude relative to mean levels.

These results suggest that perceptions of security throughout a province impact firm behavior and willingness to operate in nearby districts. In particular, this explains why it is that the Taliban frequently target urban centers and emphasizes the importance of maintaining security in provincial capitals: security in these districts impact, not only, the capitals themselves, but firms' willingness to operate in surrounding rural areas as well.

4.2 Employee Level Response to Violence

The results in the previous section characterized firm location choices and the propensity of any of the firm's employees to appear in different districts across the country. This data structure provides the most complete "footprint" of each firm's presence across all districts in the country. Econometrically, it has the advantage of allowing for an empirical strategy that directly controls for firms' differential propensity to operate in different areas while accounting for district trends. However, it does not allow us to know how an individual employee, having just experienced a terrorist attack, responded. Additionally, variation in phone usage in response to violence, discussed in Section 3.3, may be confounding our estimates. Switching to a subscriber-month panel, tracking phone usage and location of these subscribers over time, allows us to evaluate and address these concerns. We therefore create a subscriber level panel from the CDR data, defining each subscriber by its primary calling location for each month.

Employee Movement Response

First, we explore subscriber level responses to major terrorist attacks to isolate individual employee movements by estimating the following equation:

$$Y_{st} = \beta \mathbb{1}(MTA)_{dt-1} + \theta_s + \delta_t + \sigma_{dm} + \gamma_d * t + \mu_d * t^2 + \epsilon_{it} \tag{2}$$

Y_{st} is an indicator outcome for subscriber, s, in month t. $\mathbb{1}(MTA)_{dt-1}$ is the indicator of a major attack having taken place in the subscriber's location district, d, in the prior period. θ_s is a set of individual subscriber fixed effects controling for time invariant factors. σ_{dm} are a set of district-calendar month fixed effects for subscriber's district in the previous period and $\gamma_d * t$ and $\mu_d * t^2$ are district-specific linear and quadratic time trends. Throughout, we cluster our errors, ϵ_{it}, at the firm-level to account for potential firm level correlations. Our coefficient of interest is β, which we interpret as the average treatment effect of major terrorist attacks on firm presence.

Using this specification, we can test for the effect of major attacks on whether the subscriber has moved since the previous month, movement to a specific location, and having made no calls (and therefore being unable to determine their location at time, t. If firms make calls with infrequently used phones in response to terrorist attacks, this could create a false positive correlation between violence and firms that use their phones infrequently. To mitigate this risk, we impose a sample restriction and drop subscriber-months from the analysis where the subscriber has not been active in the preceding *two* time periods $t-1$ and $t-2$.

Table 5 shows these results. Column (1) of Panel A shows that a subscriber located in a district that experienced major terrorist attacks in the previous month was .24 percentage points (3%) more likely to have moved districts ($p < .01$). Columns (2)-(5) refine this outcome by specific destination, excluding those already in that destination from the sample. In column (2) we see that major attacks especially increase the likelihood that subscribers move to Kabul by .65 percentage points (27%, $p < .01$) whereas point estimates for other destinations are all also positive but smaller in magnitude and imprecisely estimated.

Panel B divides the treatment by geography. We do not see significant effects in response to major terrorist attacks in Kabul. By contrast, effects of events in capitals are large. In row (2) of column (1) we see a large increase in the likelihood of moving following major attacks in capitals. In particular, individuals are more likely to move to Kabul (33%, $p < .01$) and to other provinces (15%, $p < .01$). Movements following major attacks in rural areas are more ambiguous. We see a marginally significant reduction in the likelihood of an individual moving back to Kabul following an attack in a rural area, but estimates are imprecise given the infrequency of employees being present in rural districts at the time of attacks.

Resilience of Kabul is consistent with the nation's capital being viewed as the most secure part of the country, even after major attacks. Higher movements in response to attacks in capitals may be reflective that major attacks in these areas provide bigger updates to perceived insecurity, while those who move to and from Kabul also have the resources available to make these travel adjustments feasible.

Employee Movement Response and Firm Headquarters

While the different geographies in the previous section have distinct infrastructures and positions in the national hierarchy of security, other differentiating factors may be firm specific. We use the first six months of activity for each firm to identify their primary location and predict their headquarters, dropping these early observations from the analysis sample.[27] In Table 6, we test for heterogeneity by whether major terrorist attacks took place in a firm's predicted headquarters.

[27]This is similar to the exercise described in section 2 where, using the full data, we accurately predicted firm headquarters location for 75% of firms; here we only use the first six months for each firm.

Column (1) repeats the main result, again showing significant positive impacts of major attacks on subscribers moving. Column (2) tests for heterogeneity by primary location. Major attacks in a non-primary location increase movement by 2.4 percentage points – or 32% above the mean level – ($p < .01$) whereas those in their primary location have no discernible effect (the difference between the groups is highly significant). Column (3) splits the original treatment by geography (Kabul, provincial capitals, and rural areas) and, again, shows strongest effects in provincial capitals. Column (4) interacts each of these geographies by whether or not it is a firm's primary location. Here we find that there are strong positive effects of major attacks in Kabul for those who are not primarily based in Kabul. The effect of major attacks in capitals is smaller for those who are based there, but still positive and statistically different from zero (though not from firms based elsewhere). Finally, those who experience major attacks in rural areas that are their primary locations *reduce* their likelihood of leaving. All of these effects suggest that firm location is a key determinant of how individuals respond to major attacks while also highlighting that even events in Kabul impact willingness of firms based elsewhere to operate in the national capital.

4.3 Firm Size Heterogeneity

An important question in understanding the impact of insecurity on firm location choice is to determine if certain types of firms are more responsive than others. While our CDR data is limited in what we know about the firms, we showed in Section 3.3 that we can number of subscribers as a rough proxy for firm size. However, we drop single-subscriber firms from this analysis due to concerns that single-subscriber firms, who comprise approximately one third of the sample, are rarely actually single-employee firms and thus not giving a clear signal of firm size.[28] Splitting the remaining set of firms at the median we remain with "small" firms with 2-9 subscribers and "large" firms who have ten or more total subscribers.

[28] Appendix Figure A1 shows distributions of firm sizes for the firms in our sample whose employees were reported in other data sources. We see that the distribution of employees for single-subscriber firms sits between those of firms with 2-9 and those with 10 and more subscribers.

Table 7 explores heterogeneity by firm size in our main effects to provide insights whether large and small firms respond differently to insecurity. Panel A shows the main results from Table 3, using the "any" activity measure of firm presence split by small and large firms. We see no significant effects on small firms with point estimates close and confidence intervals covering zero. By contrast, effect sizes for large firms on activity, entry, and exit are all statistically significant with effect sizes of 3, 8, and 5 percent respectively. Panel B shows the main results on movement from Table 5 split by firm size. We see negative point estimates of 5% but no statistical significance on employee movement following exposure to a major attacks whereas employees from larger firms increase their likelihood of movement by 3% ($p < .01$). [29] Larger firms and their employees appear to be more responsive to terrorist attacks than smaller firms.

4.4 Economic Relevance

We have examined the impact of terrorist attacks on firm and employee location choices. An important question is whether these firm movements reflect meaningful changes in economic activity. The recent economics literature frequently uses nightlights as a proxy for economic activity (Henderson et al., 2012). In Appendix Table A4, we demonstrate a robust correlation between standard measures of nightlights from NOAA's VIIRS Day/Night Band Nighttime Lights and standardized versions of our principle CDR variables.

For each district-month, we calculate the number of total active firms and total active subscribers and compare this to district-level nightlights data. In columns (1)-(3) the outcome variable is the standardized average pixel-level value of nightlights in that district-month,

[29] We also explore industry heterogeneity in Tables B9 and B10. We rely on the operator's classification of firm business type into five categories: construction, trade, manufacturing, transport and other – where the final category reflects insufficient data for classification. In Appendix Table B9 we find that construction and transport firms have negative and statistically significant coefficients on Firm Active in Panel A, while the decrease in Firm Entry in Panel B is concentrated in transport, and the increase in Firm Exit is weakly observed in construction and manufacturing. Speculatively, construction and transportation activities may be associated with more mobile forms of physical capital (e.g., trucks and equipment) than other activities like trade or manufacturing. Plausibly, the differential ability to relocate valuable physical assets may affect firm responses to violence. As a caveat, we note that the version of these results using modal subscriber presence in Table B10 instead emphasizes the role of manufacturing firms.

and in columns (4)-(6) it is the standardized total pixel-level aggregate of nightlights, which allows for larger districts to contribute more.[30]

In Panel A, we find a positive relationship between number of active subscribers and these measures of aggregate economic activity: a one standard deviation increase in the number of active subscribers in a district is associated with a .37 standard deviation increase in average nightlights ($p <.01$) and a .45 standard deviation increase in total nightlights ($p <.01$), even when including district and month fixed effects in columns 3 and 6. In Panel B, we find qualitatively similar patterns when using the total number of active firms, though below traditional thresholds of statistical significance due to attenuated magnitudes. Together, we take this analysis as support for our interpretation that employee and firm movements captured in the CDR data reflect meaningful reductions in overall economic activity.

5 Conclusion

We use a novel data source, corporate mobile phone records, to explore how firms alter their location choices in response to insecurity. To our knowledge, our study is the first to use call detail records of mobile phone subscribers to understand firm behavior in a conflict-affected country, or indeed in any country. From a methodological standpoint, the validation exercises in this study suggest the promise of this approach - not as a substitute to the crucial work of collecting survey and administrative data on firms, but as a complement, particularly in fragile and conflict-affected settings where collection of firm-level data may be challenging or dangerous. By using CDR, researchers, businesses, and policymakers can extend the temporal and spatial fidelity of traditional data sources at low cost.

Using these new measures, we find a significant, 4-6% reduction in firm presence in the month immediately following a major violent event in a district. The effect is composed

[30] We calculate averages and totals over all pixels in a district, so imagine two districts that have equally-sized and equally-bright urban pixels, and differing numbers of equally-bright rural pixels. If one of these districts was larger than the other (e.g. more rural pixels, which are typically darker than urban pixels and thus have lower nightlights values), then the larger district will have a lower mean value and a higher total value than the smaller district.

of both an increase in exit by firms that were present in that district during the month of the event, and a decrease in entry of firms that were not. The negative impact on firm presence lasts for only one month at conventional significance levels, though there is suggestive evidence of longer persistence. We find evidence of regional spillovers whereby attacks in provincial capitals are followed by reductions in firm presence in surrounding rural districts.

We can also see that individual employees are more likely to move following major violent events with strongest responses in capitals where individuals increase their likelihood of moving to other provinces or to Kabul. Additionally, we find that firm-specific features also determine the patterns of displacement seen in the data, where employees are more likely to move after experiencing violence away from their firm's primary location. Finally, we show suggestive evidence of heterogeneity in response to violent outbreaks by firm size where larger firms are more likely to reduce their local presence following attacks.

These disruptions on firm operations and location choices are unlikely to be costless, delaying meetings, transactions, and deliveries. In addition to the immense human toll of conflict in Afghanistan, these distortions will serve as a direct impediment to economic activity and efficiency in poor countries affected by insecurity and an important mechanism behind the widely documented inverse relationship between insecurity and economic activity.

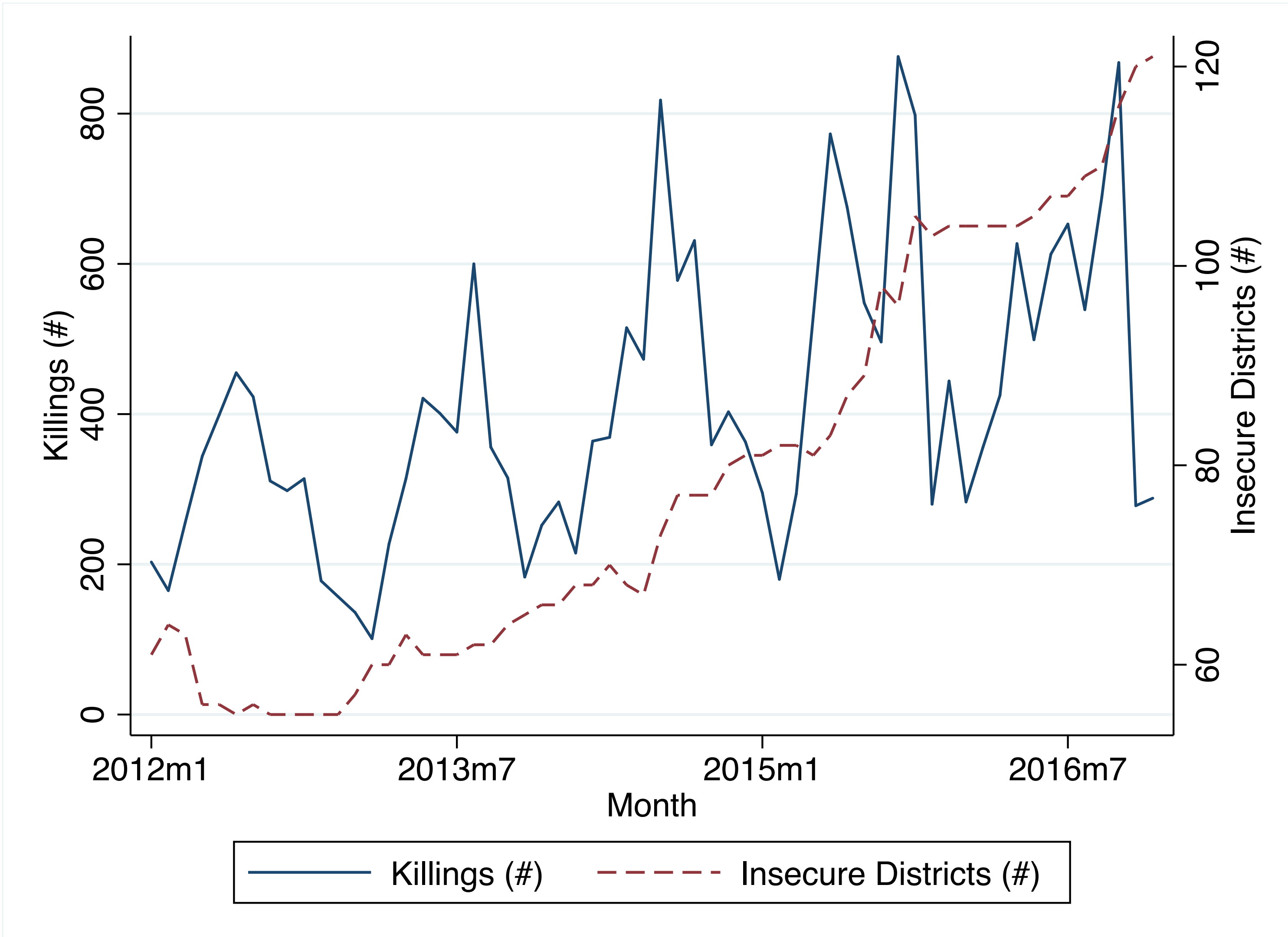
We contrast our findings with those of Besley and Mueller (2012), who estimate the economic dividends from peace using increases in housing prices in Northern Ireland at the end of The Troubles. The internal logic of their setting was a virtuous cycle of decreased killings, leading to increased asset values. Tragically, like many other conflicts in developing economies, Afghanistan suffers from a vicious cycle in which increases in insecurity lead to decreases in economic activity. These decreases in turn undermine state capacity to deliver security while challenging public confidence that the situation will improve. In both settings, the implications are that provisioning of public security is of paramount importance for private economic activity.

Figures and Tables

Figure 1: Mobile Phone Activity and the Fall of Kunduz (September 2015)

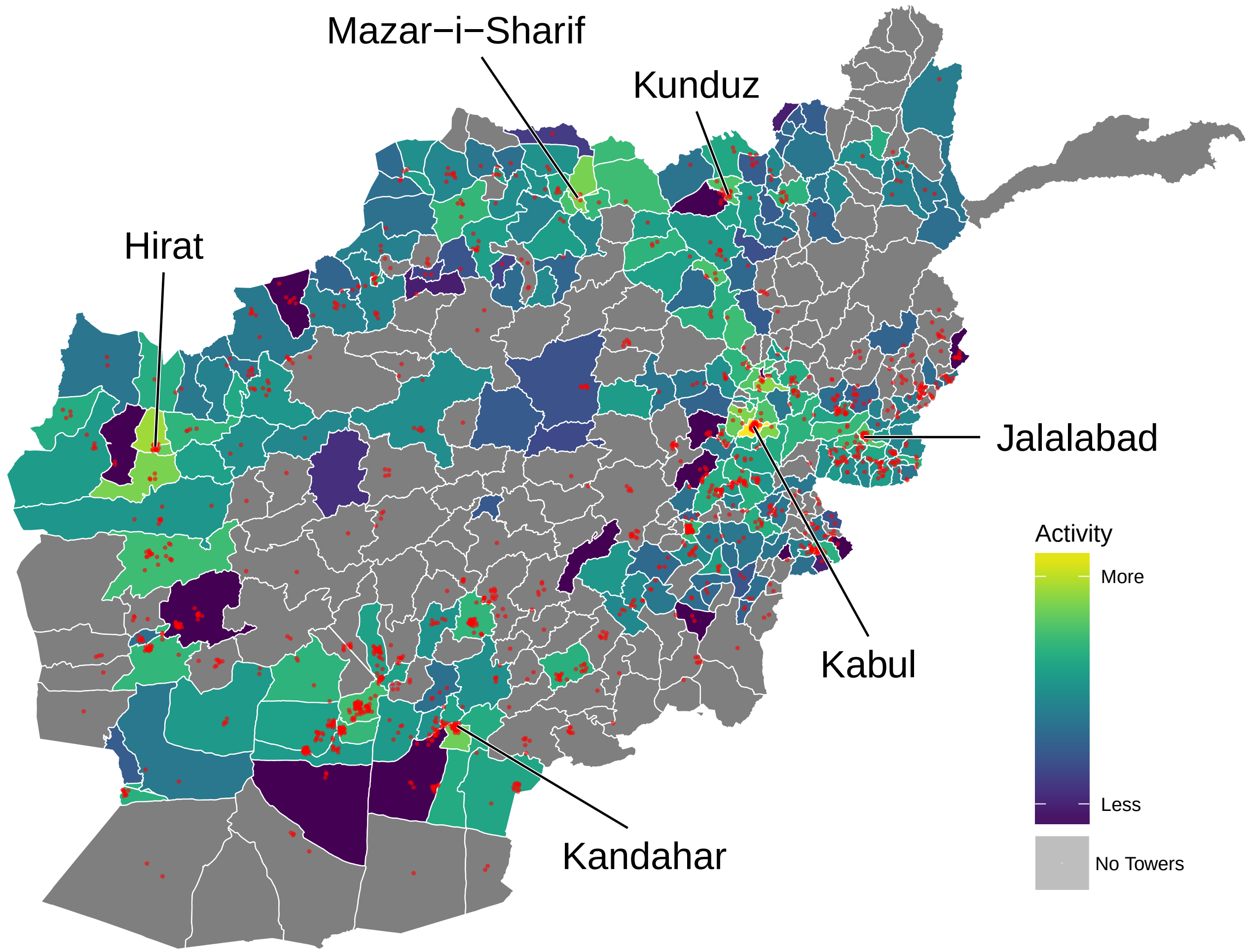
Notes: Figure shows normalized mobile phone call volumes by corporate subscribers (dashed lines) and all subscribers (solid lines) in the Kunduz region in 2015. Green lines indicate calls from numbers within 10km of the city center; Orange lines indicate calls initiated from between 10km and 70km of the city center. Vertical dashed lines mark the initial date of the Taliban's attack on Kunduz city (September 28, 2015). See Appendix C1 for additional discussion.

Figure 2: Total Killings and Insecure Districts in Afghanistan (2012-2016)



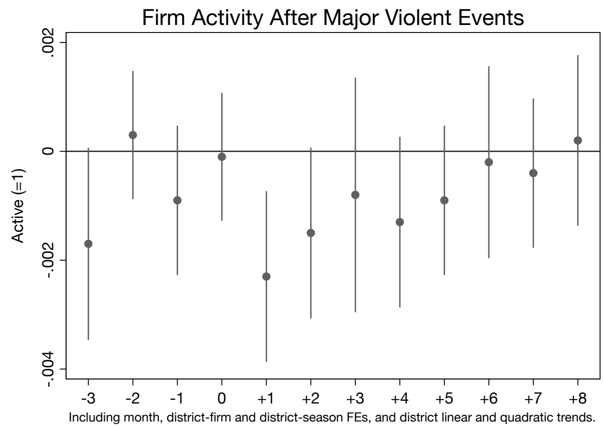
Notes: Killings reflect total confirmed fatalities in Global Terrorism Database (GTD) and Insecure Districts reflect internal security tracking data from a national survey firm. See text for details.

Figure 3: Corporate Line Activity and Killings

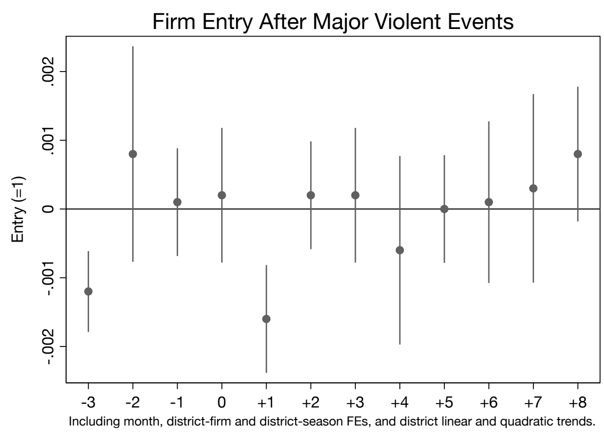


Notes: First principal component of the log number of active firms, subscribers and calls per district in corporate line mobile phone records for April 2013. Districts without mobile coverage are shown in grey. Red dots mark locations of conflirmed fatalities recorded in Global Terrorism Database (GTD) for May 2012-April 2013. See text for details.

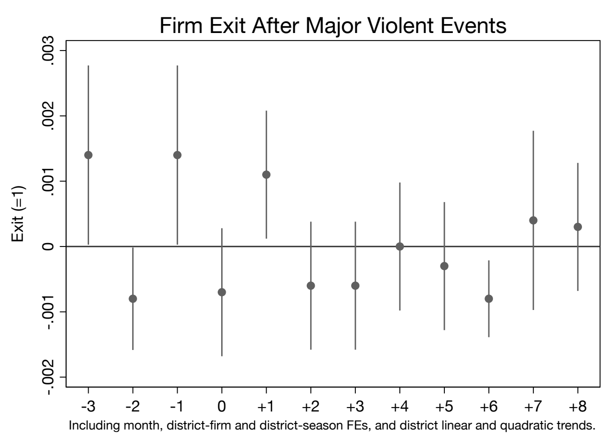
Figure 4: Major Terrorist Attacks and Firm Activity: Event Study



(a) Firm Activity



(b) Firm Entry



(c) Firm Exit

Notes: Event study coefficients from regressions of Firm Active (=1) in Panel A, Firm Entry (=1) in Panel B, and Firm Exit (=1) in Panel C on 3 leads, current term, and 8 lags of Major Terrorist Attack (=1) with time fixed effects, district-firm fixed effects, district-season fixed effects, and district linear and quadratic trends. 95% confidence intervals shown.

Table 1: Summary Statistics

	Mean	SD	Min	Med	Max
Panel A: Firm Level (N=2,306)					
Total Months Active	33.82	14.80	1	45	45
Total Districts Active	33.57	33.24	1	22	172
Mean Active Districts Per Month	8.64	15.03	0	3	163
Total Subscribers	52.26	287.71	1	4	10686
Total Calls	94140	811245	1	12087	36102988
Primary Location = Kabul (=1)	0.60	0.49	0	1	1
Primary Location = Provincial Capital (=1)	0.31	0.46	0	0	1
Primary Location = Rural (=1)	0.09	0.29	0	0	1
Active in Primary District (=1)	0.78	0.41	0	1	1
Panel B: Subscriber Level (N=115,520)					
Share of Months Active	0.500	0.368	0.022	0.429	1
Total Modal Districts	2.33	1.017	1	2	14
Likelihood of Changing Modal District (=1)	0.08	0.271	0	0	1
Panel C: District-Month Level (N=7,785)					
Total Firms	101.46	143.10	1	57	1383
Total Subscribers	506.99	1671.57	1	149	21278
Total Calls	27885	179770	1	2906	2636652
Total Killed	1.290	5.81	0	0	244
Major Terrorist Attack (=1)	0.010	0.30	0	0	1
Panel D: Firm-District-Month Level (N=15,818,428)					
Firm Active in District (=1)	0.050	0.218	0	0	1
Firm Enter District (=1)	0.014	0.117	0	0	1
Firm Exit District (=1)	0.015	0.122	0	0	1
Firm Modal Active In District (=1)	0.017	0.129	0	0	1
Firm Modal Enter District (=1)	0.003	0.055	0	0	1
Firm Modal Exit District (=1)	0.003	0.055	0	0	1

Table 2: Firm District Activity After Major Terrorist Attacks

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any calls made from district	Firm has employee who is active in district (=100)					
Major Terrorist Attack (1 lag)	13.058	-0.995**	-0.772*	-1.003**	-0.239***	-0.188***
	(10.588)	(0.477)	(0.446)	(0.497)	(0.068)	(0.063)
Mean Outcome	4.9935	4.9939	4.9939	4.9939	4.9939	4.9939
Beta/Mean	2.6151	-0.1994	-0.1547	-0.2009	-0.0479	-0.0376
Observations	15818428	15816179	15816179	15816179	15816179	15816179
Adj R2	0.0031	0.5802	0.5813	0.5817	0.5834	0.5835
Panel B: Employee based in district	Firm has employee whose primary tower is in district (=100)					
Major Terrorist Attack (1 lag)	13.234	-0.719	-0.657	-0.801	-0.147**	-0.107**
	(9.806)	(0.446)	(0.433)	(0.509)	(0.061)	(0.049)
Mean Outcome	1.7120	1.7122	1.7122	1.7122	1.7122	1.7122
Beta/Mean	7.7303	-0.4201	-0.3838	-0.4678	-0.0860	-0.0625
Observations	15818428	15816179	15816179	15816179	15816179	15816179
Adj R2	0.0091	0.6860	0.6861	0.6862	0.6878	0.6878
District-Firm FEs	No	Yes	Yes	Yes	Yes	Yes
Time FEs	No	No	Yes	Yes	Yes	Yes
District-Season FEs	No	No	No	Yes	Yes	Yes
District Lin Trends	No	No	No	No	Yes	Yes
District Quad Trends	No	No	No	No	No	Yes

Notes: Observation is a firm-district-month. Dependent variable in Panel A equals 1 if any call was made by that firm in that district-month, and 0 otherwise. Dependent variable in Panel B equals 1 if the modal calling tower for at least one of the firm's phones was in that district during that month, and 0 otherwise. Major Terrorist Attack equals 1 if previous month in top 1% of killings distribution, and 0 otherwise. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Firm District Entry and Exit After Major Terrorist Attacks

	(1) Firm Active (=100)	(2) Firm Entry (=100)	(3) Firm Exit (=100)	(4) Modal Active (=100)	(5) Modal Entry (=100)	(6) Modal Exit (=100)
Major Terrorist Attack (1 lag)	-0.188***	-0.110***	0.079*	-0.107**	-0.041*	0.060*
	(0.063)	(0.034)	(0.042)	(0.049)	(0.021)	(0.034)
Mean Outcome	4.994	1.428	1.473	1.712	0.248	0.258
Beta/Mean	-0.0376	-0.0771	0.0538	-0.0625	-0.1666	0.2325
District-Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
District-Season FEs	Yes	Yes	Yes	Yes	Yes	Yes
District Lin Trends	Yes	Yes	Yes	Yes	Yes	Yes
District Quad Trends	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15816179	15417587	15417587	15816179	15417587	15417587
Adj R2	0.5835	0.0914	0.0924	0.6878	0.0685	0.0686

Notes: Observation is a firm-district-month. Firm Entry (Exit) equals 1 if firm is absent (present) for at least 1 prior month and then present (absent) for at least 1 month, where presence is measured by at least one call made by one of the firm's phones from that district in that month. Modal Entry (Exit) is defined analogously, but where presence is measured by the modal calling tower for at least one of the firm's phones being in that district during that month. Standard errors clustered at district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Firm District Activity After Major Terrorist Attacks - Province Spillovers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Any calls made from district	Firm has employee who is active in district (=100)							
Major Attack Lag (Local)	-0.1877***	-0.1345*	-0.1419*	-0.1167	-0.1739**	-0.2936***	-0.1116	-0.1548**
	(0.0626)	(0.0747)	(0.0761)	(0.0795)	(0.0802)	(0.0800)	(0.0670)	(0.0741)
Major Attack Lag x Capital		-0.1017	-0.1013	-0.0624	-0.0713			-0.0361
		(0.1239)	(0.1343)	(0.1339)	(0.1285)			(0.1291)
Major Attack in Prov			0.0085					
			(0.0291)					
Major Attack in Prov Capital				-0.0767**				-0.0723**
				(0.0300)				(0.0293)
Major Attack in Rural Prov					0.0587*	0.0636	0.0526	0.0551*
					(0.0330)	(0.0648)	(0.0422)	(0.0320)
Mean Y	4.9939	4.9939	4.9939	4.9939	4.9939	8.9851	4.1566	4.9939
Obs	15816179	15816179	15816179	15816179	15816179	2742690	13073489	15816179
R2	0.5940	0.5940	0.5940	0.5940	0.5940	0.6649	0.5594	0.5940
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel B: Employee primarily in district	Firm has employee whose primary tower is in district (=100)							
Major Attack Lag (Local)	-0.1070**	-0.0943	-0.1018	-0.0878	-0.1137	-0.1978***	-0.0165	-0.1068
	(0.0486)	(0.0609)	(0.0643)	(0.0649)	(0.0683)	(0.0554)	(0.0261)	(0.0671)
Major Attack Lag x Capital		-0.0243	-0.0239	-0.0100	-0.0094			0.0032
		(0.0640)	(0.0621)	(0.0619)	(0.0626)			(0.0627)
Major Attack in Prov			0.0085					
			(0.0087)					
Major Attack in Prov Capital				-0.0280***				-0.0258***
				(0.0092)				(0.0087)
Major Attack in Rural Prov					0.0288***	0.0650*	0.0136*	0.0275**
					(0.0101)	(0.0328)	(0.0073)	(0.0104)
Mean Y	1.7122	1.7122	1.7122	1.7122	1.7122	5.3011	0.9592	1.7122
Obs	15816179	15816179	15816179	15816179	15816179	2742690	13073489	15816179
R2	0.6957	0.6957	0.6957	0.6957	0.6957	0.7605	0.6135	0.6957
Sample	All	All	All	All	All	Capitals	Rural	All
District-Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-Season FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Linear Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District Quadratic Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Observation is a firm-district-month. Districts are nested inside provinces. The first two independent variables capture (and control for) firm response to local violence. The next three independent variables, are the variables of interest for this table, showing province level spillovers where either the provincial capital or a non-capital district experienced a major event. Standard errors clustered at provincial level. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Individual Employee Response to Major Terrorist Attacks

Panel A:		Destination				Phone Use	
	Move	Kabul	Same Prov Capital	Same Prov Rural	Other Prov	No Call	Turn On
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Major Attack - Lag	0.236***	0.646***	0.385	0.056	0.088	0.156	0.367
	(0.090)	(0.176)	(1.048)	(0.053)	(0.062)	(0.143)	(0.362)
Sample	All	¬ Kabul	Rural	All	All	All	Off
Mean Outcome	8.009	2.360	4.253	2.287	3.125	8.091	9.285
Scaled Effect	0.029	0.274	0.091	0.024	0.028	0.019	0.040
Observations	1320919	626360	233690	1320919	1320919	1433687	1624930
Adjusted R2	0.239	0.268	0.282	0.201	0.231	0.156	0.156

Panel B:		Destination				Phone Use	
	Move	Kabul	Same Prov Capital	Same Prov Rural	Other Prov	No Call	Turn On
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Major Attack x Kabul	0.069			0.033	-0.007	0.137	0.375
	(0.090)			(0.052)	(0.062)	(0.146)	(0.396)
Major Attack x Capital	2.298***	0.790***		0.363	1.160***	0.329	0.197
	(0.394)	(0.197)		(0.223)	(0.296)	(0.454)	(0.766)
Major Attack x Rural	0.170	-1.011*	0.385	-0.186	1.268	0.813	1.173
	(1.382)	(0.578)	(1.048)	(0.770)	(1.005)	(1.337)	(1.417)
Sample	All	¬ Kabul	Rural	All	All	All	Off
Kabul Mean	3.824	-	-	1.296	6.786	2.528	8.284
Cap Mean	8.719	2.430	-	3.008	7.879	3.281	10.453
Rural Mean	14.483	2.262	4.253	3.205	10.495	3.989	11.688
Observations	1320919	694835	301817	1320919	1320919	1433687	1624930
Adjusted R2	0.239	0.294	0.289	0.201	0.231	0.156	0.156

Notes: Unit of observation is an subscriber-month. Major Attack indicates that in previous month, subscriber's modal district location experienced a major terrorist attack. Sample is restricted to subscriber's whose location for the prior two months is known. Regressions include time and subscriber's fixed effects, district presence x calendar month fixed effects for seasonality and district quadratic and linear trends. In column (7) sample is subscriber's that were *off* in previous period and is coded as 100 in the month that they first turned on. SEs clustered at the firm level.

Table 6: Subscriber Responses to Terrorist Attacks by Primary Location and Regions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	MSISDN Moves Location				Move to Prim	Move to Non-Prim	
Major Event (Lag)	0.253***	2.377***			0.892***	0.216**	-3.259***
	(0.097)	(0.431)			(0.171)	(0.086)	(0.401)
Major Event x Primary		-2.469***					4.048***
		(0.478)					(0.428)
Major Event x Kabul			0.057	2.501***			
			(0.100)	(0.596)			
Major Attack x Primary x Kabul				-2.627***			
				(0.625)			
Major Event x Capital			2.476***	2.467***			
			(0.411)	(0.433)			
Major Attack x Capital				-0.562			
				(0.775)			
Major Event x Rural			-0.437	-0.530			
			(1.488)	(1.562)			
Major Attack x Primary x Rural				-15.813**			
				(6.536)			
Sample	All	All	All	All	Non-Prim	All	All
Mean Outcome	7.581	7.544	7.649	7.544	3.919	5.807	7.989
Observations	1187114	1153521	1187114	1153521	581040	1187114	1153521
Adjusted R2	0.242	0.242	0.242	0.242	0.310	0.216	0.217

Notes: Binary outcomes are scaled by 100 for readability. Unit of observation is a subscriber-month. Major event indicates that in previous month, subscriber's modal location experienced a major terorrist attack. Sample is restricted to subscribers whose location for the prior two months is known. Regressions include month and subscriber fixed effects, district presence x calendar month fixed effects for seasonality and district quadratic and linear trends. Standard errors clustered at the firm level. Mean movement outside primary location =12.5%. in primary location =3.6%.

Table 7: Firm District Activity, Entry and Exit - Heterogeneity by Firm Size

Panel A: Firm-District-Month Panel	Small Firms (2-9 Subs)			Large Firms (10+ Subs)		
	(1) Active	(2) Enter	(3) Exit	(4) Active	(3) Enter	(4) Exit
Major Terrorist Attack (1 lag)	-0.03	-0.02	-0.03	-0.35**	-0.23***	0.17*
	(0.05)	(0.04)	(0.04)	(0.17)	(0.08)	(0.09)
Mean Outcome	2.26	0.81	0.85	11.04	2.92	2.99
Scaled Effect	-0.0142	-0.0235	-0.0353	-0.0319	-0.0771	0.0552
Observations	5791694	5648623	5648623	5532886	5386355	5386355
Adjusted R2	0.5183	0.0856	0.0862	0.5819	0.0826	0.0837

Panel B: Subscriber-Month Panel	Small Firms		Large Firms	
	(1) Move	(2) No Call	(3) Move	(4) No Call
Major Terrorist Attack (1 lag)	-0.367	0.051	0.262***	0.150
	(0.418)	(0.451)	(0.091)	(0.149)
Mean Outcome	7.262	6.600	8.058	8.178
Scaled Effect	-0.050	0.008	0.032	0.018
Observations	56663	60609	1250337	1358272
Adjusted R2	0.251	0.133	0.241	0.157

Panel (a) Notes: Observation is a firm-district-month. All regressions include month fixed effects, district-firm fixed effects, district-season fixed effects, and district linear and quadratic trends. Standard errors clustered at district level.

Panel (b) Notes: Observation is a subscriber-month. Regressions include month and subscriber fixed effects, district presence x calendar month fixed effects for seasonality and district quadratic and linear trends. Standard errors clustered at the firm level.

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Appendices - For Online Publication

A1 CDR Data Appendix

Our study relies on data from one of Afghanistan's largest private telecommunications operators. The original data contain three different types of information that are used in our empirical analysis. These data do not contain the contents of phone calls and text messages, but rather the metadata about calls and text messages – i.e., information regarding the parties involved in the communication, as well as the timing and location of the communication. As this data is sensitive and confidential, all personally identifying information was removed prior to our analysis. All research was reviewed and approved by the internal review boards at our respective institutions.

A1.1 Three Different Data Sources

Call Detail Records The central data source is *call detail records* (CDRs). These are datasets, originating from the operator's communication logs, that provide basic information about each single call (and text message) in the network. The most important features in the CDRs are: date and time of the calls, caller's unique id, receiver's id, and id of the network antenna where the call was initiated. Approximately 250 million calls and a similar amount of text messages are conducted in the network each month. As we do not observe the antenna id for messages, most of our analysis is solely based on call information.

CDRs allow us the deduce the location of every single cellphone over time, given it is used frequently. It also allows to construct callgraphs, networks of callers and receivers, and in this way analyze the location where the phones of interest are called from. We observe CDRs for 45 months, from April 2013 till December 2016, containing about 2TB of data.

Antenna Locations The second and complementary source of information, is the spatial location of network antennas. Typically several antennas are grouped into one location (such as cellphone tower) and we only use the tower location in this study. There are 1350 towers with known location, these are located in 267 of Afghanistan 398 districts covering all the cities and most of the rest of more densely populated areas.

Corporate Subscribers The final related dataset is the list of corporate phones. For each month the provider lists which phone id's are registered as business phones, and provides basic information on the firm. From this list, we exclude public and non-profit organizations, such as health, education or media groups, and in case an organization possesses multiple accounts, we merge these into a single one. We refer to these private sector numbers as "corporate subscribers".

As phone numbers occasionally move between different accounts, we disregard numbers that are assigned to multiple business accounts, do not have valid account id, or have other irregularities (this amounts to approximately 0.5% of the business phones). Over the observation period, slightly less than 200,000 phones belong to private organizations out of approximately 10 million distinct numbers in the data. This information allows us to distinguish between general call activity and business-related activity. It also permits to assess the size of the firms (in terms of corporate phones), and their geographic and temporal activity patterns. We further categorize the firms into industry-related "segments" based on the operator's internal categorization. The segments are construction (con), finance (fin), IT and telecommunication (it), manufacturing and trade (trade), security (sec), transportation (trans), and "other". Note that we cannot use the standard ISIC codes because the operator's internal classification is based on a different categorization.

A1.2 Data Processing

A1.2.1 Constructing Panel Data

Our central empirical approach relies on monthly panel data on firm activity by Afghanistan districts, and on similar panels defined on quarters, weeks, and provinces. We count all calls and distinct active subscribers by each firm in each spatio-temporal cell. Based on whether the firm was active in the given cell, we also define it's binary "activity" in the cell.

As expected, activity distributions by firms show a prominent right tail while the activity is rougly constant in time. The median value of firm size (subscribers it posesses) is 4, while it's mean is 52.26 and the maximum value is 10686.

For district-based approach, we further aggregate the firm level data on districts, separately counting for call activity for different activity segments and firm size classes. This forms our base data to describe firm activity. Again, the distributions are highly skewed with Kabul region clearly dominating the the spatial picture but the other major cities are also clearly present.

A1.2.2 Tower-Level Data

In order to analyze short-term responses to particular events (such as the Battle of Kunduz), we count the total number of daily calls per network tower. We compute two separate sets of values: one for all calls (including non-corporate subscriber calls) for analyzing the general population behavior, and the other for corporate subscriber calls, to see if there are any distinct differences between business and general behavior. We do not select non-corporate subscribers for the figure for two reasons. First, as the number of corporate subscribers is only 2% of the total subscribers in the data, it makes only a little difference; and second, presumably a substantial number of phones that are primarily used for business purposes are not registered as such. While we have no information on private use of registered business phones but during quickly evolving disruptive events, like the Battle of Kunduz, private usage may even dominate.

A1.2.3 Individual Locations

We use location of individual firms and towers for two purposes. First, in case of validating the location of firm's headquarters and regional offices, we calculate the modal district (in terms of calls made) of each phone associated with the given firm. We then order the resulting districts by the number of phones in each, and compare the top 5 districts to the recorded locations of headquarters and regional offices in other administrative and survey data sources. Second, for the Kunduz empirical case analysis we also use an approximation of individual subscriber locations. We compute centroid of cellphone towers where the phone is active during the day-of-interest, while weighting the tower locations by the number of calls by the phone through that respective tower.

A1.3 Figure Explanations

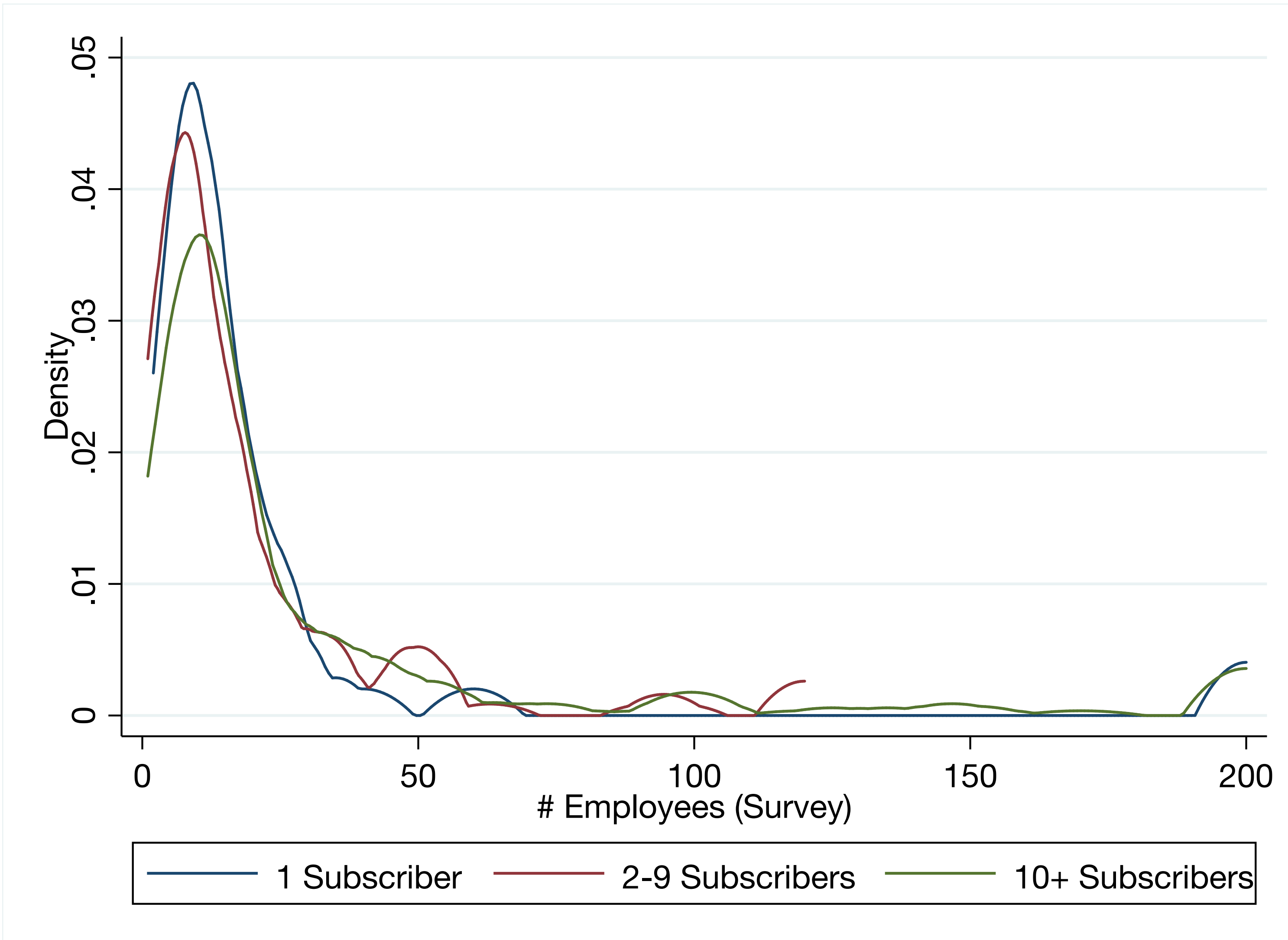
Figure 3: Corporate Line Activity and Killings This depict a district-month call activity principal component. PC is calculated as the PC of log(1 + active firms), log(1 + active subscribers) and log(1 + # of calls) across the district-month cells. The plots depict the PC for April 2013 and also includes GTD kills for May 2012-April 2013 as small red dots. The dots are jittered to make their density more easily recognizable.

Figure C1: Calling Activity Inside and Outside Kunduz (2015 & 2016) Indicate the total usage of cellphone towers (count of outgoing calls) by all, and by business phones during 2×12 week window. Towers up to 10km from the center are green, 10-70km orange. All phones include all phones, including corporate subscribers. The center is defined as the centroid of the towers in the corresponding district (in practice it locates the center into the major city). The usage is normalized with respect to the mean and standard deviation of the corresponding time series. The normalization is performed over 12-week window.

Figure C2: Mobile Tower Locations near Kunduz The maps of the towers for the corresponding usage graphs. Towers up to 10km from the center are green, 10-70km orange, same colors as used on the usage graphs. The center is defined as the centroid of the towers in the corresponding district (in practice it locates the center into the major city).

Figure C3: Daily Locations of Corporate Lines Subscribers - Kunduz 2015 We plot the centroid of distinct corporate subscribers that are active in the region during the given day. We select a sample of the 150 subscribers who are present on the largest number of days during the period of interest. The days are a) 1 week before the attack; b) 2015-09-28 – the day of attack which occured early morning; c) one week after the attack (during the ongoing battle); and e) 1 month after the attack when Taliban had retreated from the city. In all, there are 6727 phones active in the region between August 15th and November 15th, 2015, but on a given day the number is lower. The centroid is average of the location of the towers the phone has made at least one call, weighted by the number of calls in these towers.

Figure A1: Employee Size Distributions by Total Subscribers



Notes: Employee data from original survey sample (n=317). Windsorizing number of employees at 200.

Table A1: Survey Instrument Representativeness Table

	Enterprise Survey (Survey Vars)	CDR Sample (CDR Vars)	CDR Surveyed Sample (CDR Vars)	Survey Sample (Survey Vars)
Num Employees At Present	21.375	52.261	54.788	33.970
Sector Trade (=1)	0.397	0.112	0.103	0.073
Sector Manufacturing (=1)	0.355	0.133	0.379	0.271
Sector Construction (=1)	0.104	0.190	0.185	0.268
Sector Transport (=1)	0.144	0.118	0.106	0.148
Sector Security (=1)	0.000	0.015	0.012	0.010
Sector Finance (=1)	N/A	0.012	0.017	0.033
Sector Information Technology (=1)	N/A	0.006	0.010	N/A
Sector Other (=1)	0.000	0.410	0.187	0.178
HQ in Kabul (=1)	0.404	0.614	0.599	0.700
HQ in Hirat (=1)	0.192	0.167	0.202	0.200
HQ in Balkh (=1)	0.137	0.082	0.108	0.079
HQ in Nangahar (=1)	0.146	0.034	0.027	0.020
HQ in Kandahar (=1)	0.122	0.023	0.010	0.000
HQ in Kunduz (=1)	N/A	0.020	0.015	0.002
N	416	2306	406	406

Notes: Mean values reported for each variable. Enterprise survey means reweighted to reflect nationally representative population. Columns 2 and 3 utilize CDR variables. CDR "Num Employees At Present" calculated based on total MSISDNS for each firm in 2016. CDR sector code was calculated based on a category provided by the phone company, matched to the corresponding two-digit ISIC code (Rev. 4). CDR headquarters are calculated using the firm's first modal district as a proxy. CDR Surveyed refers to the firms in CDR who were surveyed. Columns 1 and 4 utilize survey variables. 'Sectors' and 'Number of Employees at Present' are self-reported, as provided by each survey. World Bank (Enterprise) sector code was calculated based on the four-digit ISIC code (Rev. 3) reported for the primary good or service produced by each firm. Survey headquarters are self-reported, as provided by each survey.

Table A2: Location Validation

Panel A: Headquarters		% HQ Match	
	Obs	Top 1 Modal "Primary"	Top 5 Modal
AISA	110	82.73	92.73
CBR	934	73.34	83.30
Survey	406	79.80	88.18
All Combined	1119	74.71	84.81

Panel B: All Offices			
	Obs	Num of Offices	% HQ Match Top 5 Modal
Survey 2017 Response	406	2.71	62.41
Survey 2014 Response	395	2.39	64.87
Survey All	801	2.55	61.88

Notes: Observation is a firm in Panel A and a firm-year in Panel B.

Table A3: Employee Size Validation

	Number of Employees				Number of Employees			
Panel A: Levels								
Subscribers	0.789**	0.569**	0.315**	0.104	0.793**	0.631***	0.346**	0.056
	(0.346)	(0.231)	(0.159)	(0.182)	(0.350)	(0.224)	(0.156)	(0.160)
Trim	No Trim				Drop Single Subscriber Firms			
Sample	2014 IBES	2016 Survey	All Survey	All Survey	2014 IBES	2016 Survey	All Survey	All Survey
Mean Y	41.79	40.10	33.72	33.72	45.31	34.02	30.56	30.56
# Obs	190	312	580	580	157	273	500	500
Year FE	-	-	NO	YES	-	-	NO	YES
Orgid FE	-	-	NO	YES	-	-	NO	YES
R2	0.2650	0.0351	0.0212	0.7253	0.2711	0.1983	0.0924	0.8209

	Log Employees				Log Employees			
Panel B: Logs								
Log Subscribers	0.220***	0.231***	0.169***	0.071	0.239***	0.274***	0.188***	0.069
	(0.068)	(0.047)	(0.040)	(0.100)	(0.077)	(0.049)	(0.044)	(0.100)
Trim	No Trim				Drop Single Subscriber Firms			
Sample	2014 IBES	2016 Survey	All Survey	All Survey	2014 IBES	2016 Survey	All Survey	All Survey
Mean Y	2.63	2.68	2.57	2.57	2.68	2.69	2.60	2.60
# Obs	190	312	580	580	157	273	500	500
Year FE	-	-	NO	YES	-	-	NO	YES
Orgid FE	-	-	NO	YES	-	-	NO	YES
R2	0.0713	0.0975	0.0538	0.8675	0.0766	0.1295	0.0611	0.8594

Notes: "Number Employees" is self-reported survey data from the Integrated Business Enterprise Survey (IBES) in early 2014 and in our original survey data from early 2017, where in the latter source measured both current employees and employees from three years prior. "2017 Survey" sample only includes response to current employees question, while "All Survey" sample includes responses to both current employees and employees from three years prior. Total Subscribers is the count of unique MSISDNs per firm in the CDR data and is calculated from January - March 2014 for the IBES regressions in column (1) and (5), from October-December 2016 for the 2017 Survey regressions in column (2) and (6), and from October-December 2013 and October-December 2016 in columns (3), (4), (7), (8). The top 1% of Total Subscribers values are winsorized in all columns, and all single subscriber firms are dropped in columns (5)-(8). *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Aggregate Economic Activity Validation - Nightlights

	Average Nightlights (z-score)			Total Nightlights (z-score)		
Panel A: Total Active Subscribers	(1)	(2)	(3)	(4)	(5)	(6)
Total Active Subscribers (z-score)	0.57***	0.57***	0.37**	0.65***	0.65***	0.45**
	(0.04)	(0.04)	(0.15)	(0.08)	(0.08)	(0.19)
Constant	-0.00	0.08	0.08***	-0.00	0.08	0.08**
	(0.05)	(0.06)	(0.03)	(0.05)	(0.08)	(0.04)
R-Squared	0.321	0.390	0.817	0.420	0.430	0.889
# Districts	173	173	173	173	173	173
# Observations	7785	7785	7785	7785	7785	7785
Year-Month FE	NO	YES	YES	NO	YES	YES
District FE	NO	NO	YES	NO	NO	YES

	Average Nightlights (z-score)			Total Nightlights (z-score)		
Panel B: Total Active Firms	(1)	(2)	(3)	(4)	(5)	(6)
Total Active Firms (z-score)	0.46***	0.45***	0.21	0.61***	0.61***	0.18*
	(0.17)	(0.17)	(0.13)	(0.15)	(0.15)	(0.10)
Constant	-0.00	0.05	0.06***	0.00	0.04	0.06**
	(0.06)	(0.07)	(0.02)	(0.05)	(0.08)	(0.03)
R-Squared	0.207	0.275	0.817	0.374	0.385	0.888
# Districts	173	173	173	173	173	173
# Observations	7785	7785	7785	7785	7785	7785
Year-Month FE	NO	YES	YES	NO	YES	YES
District FE	NO	NO	YES	NO	NO	YES

Notes: Observation is a district-month. See paper text for details. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

B1 Additional Tests of Robustness

Table B1: Firm District Activity - Alternative Violence Definitions

	(1)	(2)	(3)	(4)	(5)	(6)
	Firm has employee who is active in district (=100)					
Number of Deaths (1 lag)	-0.0041***					
	(0.0008)					
1-3 Deaths (0-50%)		-0.0559***				
		(0.0161)				
4-7 Deaths (50-75%)		-0.0181				
		(0.0276)				
8-22 Deaths (75-95%)		-0.0449				
		(0.0298)				
23+ Deaths (>95%)		-0.2094***				
		(0.0663)				
Deaths/100K people			-0.0021***			
			(0.0008)			
0-3.5 Deaths/100K Pop (0-50%, > 0)				-0.0418**		
				(0.0183)		
3.5-8.75 Deaths/100K Pop (50-75%, > 0)				-0.0562***		
				(0.0213)		
8.75-30 Deaths/100K Pop (75-95%, > 0)				-0.0547*		
				(0.0322)		
>30 Deaths/100K Pop (>95%, > 0)				-0.0973		
				(0.0613)		
Biggest Event in District During Study					-0.0625	
					(0.0426)	
Biggest Two Events in District During Study						-0.0502
						(0.0314)
Mean Outcome	4.9939	4.9939	4.9939	4.9939	4.9958	4.9958
Observations	15816179	15816179	15816179	15816179	15359064	15359064
Adj R2	0.5835	0.5835	0.5835	0.5835	0.5856	0.5856
District-Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
District-Season FEs	Yes	Yes	Yes	Yes	Yes	Yes
District Linear Trends	Yes	Yes	Yes	Yes	Yes	Yes
District Quadratic Trends	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Observation is a firm-district-month. Dependent variable is indicator for whether a firm made any calls in a given district and month. All independent variables represent one month lagged measures of violence. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Firm District Activity After Major Terrorist Attacks (Log Active Subscribers)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any calls made from district	Log subscribers who are active in district +1					
Major Terrorist Attack (1 lag)	0.2197	-0.0152*	-0.0127	-0.0166	-0.0030***	-0.0022***
	(0.1741)	(0.0090)	(0.0086)	(0.0100)	(0.0009)	(0.0007)
Mean Outcome	0.0575	0.0575	0.0575	0.0575	0.0575	0.0575
Beta/Mean	3.8200	-0.2635	-0.2215	-0.2886	-0.0523	-0.0390
Observations	15818428	15816179	15816179	15816179	15816179	15816179
Adj R2	0.0046	0.7772	0.7779	0.7782	0.7802	0.7802
Panel B: Employee based in district	Log subscribers whose primary tower is in district +1					
Major Terrorist Attack (1 lag)	0.2122	-0.0117	-0.0109	-0.0134	-0.0018**	-0.0012**
	(0.1579)	(0.0084)	(0.0081)	(0.0096)	(0.0009)	(0.0005)
Mean Outcome	0.0206	0.0206	0.0206	0.0206	0.0206	0.0206
Beta/Mean	10.2993	-0.5675	-0.5287	-0.6521	-0.0856	-0.0594
Observations	15818428	15816179	15816179	15816179	15816179	15816179
Adj R2	0.0108	0.8292	0.8294	0.8295	0.8319	0.8319
District-Firm FEs	No	Yes	Yes	Yes	Yes	Yes
Time FEs	No	No	Yes	Yes	Yes	Yes
District-Season FEs	No	No	No	Yes	Yes	Yes
District Lin Trends	No	No	No	No	Yes	Yes
District Quad Trends	No	No	No	No	No	Yes

Notes: Observation is a firm-district-month, and panel is constructed using only calls made from 9am-5pm local time on Sunday-Thursday (the Afghan work week). Dependent variable in Panel A equals 1 if any call was made by that firm in that district-month, and 0 otherwise. Dependent variable in Panel B equals 1 if the modal calling tower for at least one of the firm's phones was in that district during that month, and 0 otherwise. Major Terrorist Attack equals 1 if previous month in top 1% of killings distribution, and 0 otherwise. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B3: Firm District Activity After Major Terrorist Attacks (Unbalanced Panel)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any calls made from district	Firm has employee who is active in district (=1)					
Major Terrorist Attack (1 lag)	0.0850	-0.0075**	-0.0054*	-0.0072*	-0.0014**	-0.0013**
	(0.0773)	(0.0034)	(0.0032)	(0.0038)	(0.0006)	(0.0005)
Mean Outcome	0.0405	0.0405	0.0405	0.0405	0.0405	0.0405
Beta/Mean	2.0984	-0.1858	-0.1325	-0.1778	-0.0342	-0.0315
Observations	21278083	21274534	21274534	21274534	21274534	21274534
Adj R2	0.0018	0.5742	0.5751	0.5755	0.5772	0.5773
Panel B: Employee based in district	Firm has employee whose primary tower is in district (=1)					
Major Terrorist Attack (1 lag)	0.0876	-0.0052*	-0.0047	-0.0059	-0.0011**	-0.0009**
	(0.0711)	(0.0031)	(0.0030)	(0.0037)	(0.0005)	(0.0004)
Mean Outcome	0.0138	0.0138	0.0138	0.0138	0.0138	0.0138
Beta/Mean	6.3406	-0.3750	-0.3373	-0.4306	-0.0774	-0.0668
Observations	21278083	21274534	21274534	21274534	21274534	21274534
Adj R2	0.0056	0.6762	0.6763	0.6764	0.6779	0.6780
District-Firm FEs	No	Yes	Yes	Yes	Yes	Yes
Time FEs	No	No	Yes	Yes	Yes	Yes
District-Season FEs	No	No	No	Yes	Yes	Yes
District Lin Trends	No	No	No	No	Yes	Yes
District Quad Trends	No	No	No	No	No	Yes

Notes: Observation is a firm-district-month, and panel is constructed to include all district-month observations with at least 28 days of cell coverage. Dependent variable in Panel A equals 1 if any call was made by that firm in that district-month, and 0 otherwise. Dependent variable in Panel B equals 1 if the modal calling tower for at least one of the firm's phones was in that district during that month, and 0 otherwise. Major Terrorist Attack equals 1 if previous month in top 1% of killings distribution, and 0 otherwise. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B4: Firm District Activity After Major Terrorist Attacks (Work Week Panel)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any calls made from district	Firm has employee who is active in district (=1)					
Major Terrorist Attack (1 lag)	0.1326	-0.0093*	-0.0074	-0.0098*	-0.0023***	-0.0019***
	(0.1040)	(0.0049)	(0.0046)	(0.0053)	(0.0007)	(0.0006)
Mean Outcome	0.0388	0.0388	0.0388	0.0388	0.0388	0.0388
Beta/Mean	3.4169	-0.2389	-0.1914	-0.2513	-0.0582	-0.0480
Observations	15722932	15721029	15721029	15721029	15721029	15721029
Adj R2	0.0041	0.5722	0.5729	0.5731	0.5747	0.5747
Panel B: Employee based in district	Firm has employee whose primary tower is in district (=1)					
Major Terrorist Attack (1 lag)	0.1313	-0.0070	-0.0063	-0.0079	-0.0013	-0.0008
	(0.0970)	(0.0047)	(0.0045)	(0.0053)	(0.0008)	(0.0007)
Mean Outcome	0.0165	0.0165	0.0165	0.0165	0.0165	0.0165
Beta/Mean	7.9754	-0.4229	-0.3854	-0.4777	-0.0773	-0.0486
Observations	15722932	15721029	15721029	15721029	15721029	15721029
Adj R2	0.0093	0.6746	0.6748	0.6749	0.6766	0.6766
District-Firm FEs	No	Yes	Yes	Yes	Yes	Yes
Time FEs	No	No	Yes	Yes	Yes	Yes
District-Season FEs	No	No	No	Yes	Yes	Yes
District Lin Trends	No	No	No	No	Yes	Yes
District Quad Trends	No	No	No	No	No	Yes

Notes: Observation is a firm-district-month, and panel is constructed using only calls made from 9am-5pm local time on Sunday-Thursday (the Afghan work week). Dependent variable in Panel A equals 1 if any call was made by that firm in that district-month, and 0 otherwise. Dependent variable in Panel B equals 1 if the modal calling tower for at least one of the firm's phones was in that district during that month, and 0 otherwise. Major Terrorist Attack equals 1 if previous month in top 1% of killings distribution, and 0 otherwise. Standard errors clustered at district level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B5: Firm District Entry and Exit After Major Terrorist Attacks (Without District Trends)

	(1) Firm Active (=100)	(2) Firm Entry (=100)	(3) Firm Exit (=100)	(4) Modal Active (=100)	(5) Modal Entry (=100)	(6) Modal Exit (=100)
Major Terrorist Attack (1 lag)	-1.003**	-0.164***	0.007	-0.801	-0.066**	0.030
	(0.497)	(0.049)	(0.053)	(0.509)	(0.027)	(0.023)
Mean Outcome	4.994	1.428	1.473	1.712	0.247	0.258
Beta/Mean	-0.2009	-0.1150	0.0046	-0.4678	-0.2662	0.1149
District-Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
District Season FEs	Yes	Yes	Yes	Yes	Yes	Yes
District Lin Trends	No	No	No	No	No	No
Dist Quad Trends	No	No	No	No	No	No
Observations	15816179	15417587	15417587	15816179	15417587	15417587
Adj R2	0.5817	0.0910	0.0920	0.6862	0.0685	0.0685

Notes: Observation is a firm-district-month. Firm Entry (Exit) equals 1 if firm is absent (present) for at least 1 prior month and then present (absent) for at least 1 month, where presence is measured by at least one call made by one of the firm's phones from that district in that month. Modal Entry (Exit) is defined analogously, but where presence is measured by the modal calling tower for at least one of the firm's phones being in that district during that month. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B6: Firm District Activity After Major Terrorist Attacks - Province Spillovers (No Trends)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any calls made from district	Firm has employee who is active in district (=100)					
Major Terrorist Attack (1 lag)	-1.0031**	-0.4553*	-0.2502	-0.3363	-0.4345	-0.3010
	(0.4827)	(0.2496)	(0.2143)	(0.2020)	(0.2917)	(0.2386)
Major Attack x (District=Capital)		-1.0486**	-1.0525**	-0.7906*	-1.0634**	-0.8134**
		(0.4511)	(0.4508)	(0.3878)	(0.4270)	(0.3695)
Major Attack Anywhere in Province			-0.2354**			
			(0.0951)			
Major Attack in Provincial Capital				-0.5068***		-0.5103***
				(0.1561)		(0.1512)
Major Attack in Province Outside Capital					-0.0315	-0.0521
					(0.1042)	(0.1006)
Mean Outcome	4.9939	4.9939	4.9939	4.9939	4.9939	4.9939
Observations	15816179	15816179	15816179	15816179	15816179	15816179
Adj R2	0.5923	0.5923	0.5923	0.5923	0.5923	0.5923
Panel B: Employee based in district	Firm has employee whose primary tower is in district (=100)					
Major Terrorist Attack (1 lag)	-0.8008	-0.3610	-0.3534	-0.3423	-0.3854	-0.3651
	(0.5253)	(0.2507)	(0.2522)	(0.2446)	(0.2714)	(0.2659)
Major Attack x (District=Capital)		-0.8418*	-0.8420*	-0.8012*	-0.8245**	-0.7865*
		(0.4150)	(0.4148)	(0.4096)	(0.3973)	(0.3923)
Major Attack Anywhere in Province			-0.0087			
			(0.0315)			
Major Attack in Provincial Capital				-0.0798***		-0.0776**
				(0.0279)		(0.0294)
Major Attack in Province Outside Capital					0.0368	0.0337
					(0.0532)	(0.0533)
Mean Outcome	1.7122	1.7122	1.7122	1.7122	1.7122	1.7122
Observations	15816179	15816179	15816179	15816179	15816179	15816179
Adj R2	0.6941	0.6941	0.6941	0.6941	0.6941	0.6941
District-Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
District-Season FEs	Yes	Yes	Yes	Yes	Yes	Yes
District Linear Trends	No	No	No	No	No	No
District Quadratic Trends	No	No	No	No	No	No

Notes: Observation is a firm-district-month. Districts are nested inside provinces. The first two independent variables capture (and control for) firm response to local violence. The next three independent variables, are the variables of interest for this table, showing province level spillovers where either the provincial capital or a non-capital district experienced a major event. Standard errors clustered at provincial level. *** p<0.01, ** p<0.05, * p<0.1.

Table B7: Firm District Activity, Entry & Exit After Major Attacks - Leads & Lags

	(1) Firm Active (=1)	(2) Firm Entry (=1)	(3) Firm Exit (=1)	(4) Modal Active (=1)	(5) Modal Entry (=1)	(6) Modal Exit (=1)
Lead 3	-0.0017*	-0.0012***	0.0014**	-0.0017	-0.0006**	0.0009*
	(0.0009)	(0.0003)	(0.0007)	(0.0011)	(0.0003)	(0.0005)
Lead 2	0.0003	0.0008	-0.0008**	-0.0009	0.0003	-0.0004*
	(0.0006)	(0.0008)	(0.0004)	(0.0006)	(0.0004)	(0.0002)
Lead 1	-0.0009	0.0001	0.0014**	-0.0009	0.0000	0.0003
	(0.0007)	(0.0004)	(0.0007)	(0.0007)	(0.0001)	(0.0003)
Current	-0.0001	0.0002	-0.0007	-0.0004	0.0003	-0.0005
	(0.0006)	(0.0005)	(0.0005)	(0.0003)	(0.0004)	(0.0003)
Lag 1	-0.0023***	-0.0016***	0.0011**	-0.0014*	-0.0004	0.0006*
	(0.0008)	(0.0004)	(0.0005)	(0.0008)	(0.0003)	(0.0003)
Lag 2	-0.0015*	0.0002	-0.0006	-0.0015	-0.0001	-0.0002
	(0.0008)	(0.0004)	(0.0005)	(0.0012)	(0.0003)	(0.0004)
Lag 3	-0.0008	0.0002	-0.0006	-0.0013	0.0002	-0.0001
	(0.0011)	(0.0005)	(0.0005)	(0.0010)	(0.0007)	(0.0004)
Lag 4	-0.0013	-0.0006	-0.0000	-0.0012*	0.0000	0.0001
	(0.0008)	(0.0007)	(0.0005)	(0.0007)	(0.0005)	(0.0002)
Lag 5	-0.0009	0.0000	-0.0003	-0.0010**	-0.0001	-0.0006
	(0.0007)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0005)
Lag 6	-0.0002	0.0001	-0.0008**	-0.0001	0.0001	-0.0009***
	(0.0009)	(0.0006)	(0.0003)	(0.0005)	(0.0004)	(0.0002)
Lag 7	-0.0004	0.0003	0.0004	-0.0009	-0.0006**	0.0002
	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0003)	(0.0007)
Lag 8	0.0002	0.0008	0.0003	-0.0004	0.0002	-0.0002
	(0.0008)	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0003)
Mean Outcome	0.0508	0.0146	0.0150	0.0174	0.0025	0.0026
Observations	14627150	14232364	14232364	14627150	14232364	14232364
Adj R2	0.5865	0.0924	0.0927	0.6927	0.0694	0.0697

Notes: Observation is a firm-district-month. All regressions include time fixed effects, district-firm fixed effects, district-season fixed effects, and district linear and quadratic trends. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B8: Firm District Activity, Entry and Exit - Heterogeneity by Firm Size (Modal)

	(1)	(2)	(3)	(4)	(5)
Panel A	Modal Active in District (=1)				
Major Terrorist Attack (1 lag)	-0.0011**	-0.0012**	-0.0007	-0.0005	-0.0020**
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0010)
Firm Size Sample	All	No Single	Single	Small	Large
Mean Outcome	0.0171	0.0225	0.0036	0.0068	0.0389
Beta/Mean	-0.0625	-0.0539	-0.2061	-0.0709	-0.0511
Observations	15816179	11324580	4491599	5791694	5532886
Adj R2	0.6878	0.6827	0.7475	0.7645	0.6631
Panel B	Modal Entry into District (=1)				
Major Terrorist Attack (1 lag)	-0.0004*	-0.0004	-0.0004	0.0002	-0.0011*
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0006)
Firm Size Sample	All	No Single	Single	Small	Large
Mean Outcome	0.0025	0.0033	0.0004	0.0008	0.0060
Beta/Mean	-0.1666	-0.1250	-1.0489	0.3194	-0.1850
Observations	15417587	11034978	4382609	5648623	5386355
Adj R2	0.0685	0.0670	0.0815	0.0743	0.0634
Panel C	Modal Exit from District (=1)				
Major Terrorist Attack (1 lag)	0.0006*	0.0006	0.0007**	0.0005	0.0006
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0006)
Firm Size Sample	All	No Single	Single	Small	Large
Mean Outcome	0.0026	0.0034	0.0005	0.0008	0.0061
Beta/Mean	0.2325	0.1634	1.4257	0.5748	0.1028
Observations	15417587	11034978	4382609	5648623	5386355
Adj R2	0.0686	0.0671	0.0807	0.0726	0.0636

Notes: Observation is a firm-district-month. Firm sample is all firms in column 1, firms with 2 or more subscribers in column 2, single subscriber firms in column 3, firms with 2-9 total subscribers in column 4, and firms with 10 or more total subscribers in column 5. All regressions include month fixed effects, district-firm fixed effects, district-season fixed effects, and district linear and quadratic trends. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B9: Firm District Activity, Entry and Exit - Heterogeneity by Firm Industry

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Firm Active in District (=1)					
Major Terrorist Attack (1 lag)	-0.0019***	-0.0041***	0.0000	-0.0001	-0.0031*	-0.0016***
	(0.0006)	(0.0014)	(0.0013)	(0.0014)	(0.0017)	(0.0006)
Firm Industry Sample	All	Construction	Trade	Manufacturing	Transport	Other
Mean Outcome	0.0499	0.0503	0.0441	0.0517	0.0557	0.0492
Beta/Mean	-0.0376	-0.0829	0.0008	-0.0023	-0.0624	-0.0313
Observations	15816179	3088396	1874801	2017872	1915456	6919654
Adj R2	0.5835	0.5553	0.5539	0.5903	0.6042	0.5955
Panel B	Firm Entry into District (=1)					
Major Terrorist Attack (1 lag)	-0.0011***	-0.0012	-0.0001	-0.0010	-0.0029***	-0.0009*
	(0.0003)	(0.0011)	(0.0010)	(0.0007)	(0.0011)	(0.0004)
Firm Industry Sample	All	Construction	Trade	Manufacturing	Transport	Other
Mean Outcome	0.0143	0.0155	0.0139	0.0148	0.0152	0.0134
Beta/Mean	-0.0771	-0.0828	-0.0062	-0.0682	-0.2042	-0.0613
Observations	15417587	3013660	1829994	1964588	1868573	6740772
Adj R2	0.0914	0.0890	0.0928	0.0922	0.0925	0.0916
Panel C	Firm Exit from District (=1)					
Major Terrorist Attack (1 lag)	0.0008*	0.0013*	0.0004	0.0015*	0.0016	0.0002
	(0.0004)	(0.0008)	(0.0011)	(0.0008)	(0.0011)	(0.0005)
Firm Industry Sample	All	Construction	Trade	Manufacturing	Transport	Other
Mean Outcome	0.0147	0.0162	0.0147	0.0151	0.0157	0.0137
Beta/Mean	0.0538	0.0904	0.0257	0.0994	0.1116	0.0165
Observations	15417587	3013660	1829994	1964588	1868573	6740772
Adj R2	0.0924	0.0901	0.0945	0.0932	0.0929	0.0925

Notes: Observation is a firm-district-month. All regressions include month fixed effects, district-firm fixed effects, district-season fixed effects, and district linear and quadratic trends. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B10: Firm District Activity, Entry and Exit - Heterogeneity by Firm Industry (Modal)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	Modal Active in District (=1)					
Major Terrorist Attack (1 lag)	-0.0011**	-0.0014	0.0002	-0.0023***	-0.0003	-0.0011**
	(0.0005)	(0.0011)	(0.0009)	(0.0006)	(0.0007)	(0.0004)
Firm Industry Sample	All	Construction	Trade	Manufacturing	Transport	Other
Mean Outcome	0.0171	0.0159	0.0129	0.0166	0.0183	0.0186
Beta/Mean	-0.0625	-0.0835	0.0132	-0.1317	-0.0191	-0.0655
Observations	15816179	3088396	1874801	2017872	1915456	6919654
Adj R2	0.6878	0.6672	0.7062	0.6919	0.6832	0.6927
Panel B	Modal Entry into District (=1)					
Major Terrorist Attack (1 lag)	-0.0004*	0.0006	0.0003	-0.0010**	-0.0003	-0.0009***
	(0.0002)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.0003)
Firm Industry Sample	All	Construction	Trade	Manufacturing	Transport	Other
Mean Outcome	0.0025	0.0025	0.0017	0.0024	0.0028	0.0026
Beta/Mean	-0.1666	0.2485	0.1377	-0.3958	-0.1331	-0.3758
Observations	15417587	3013660	1829994	1964588	1868573	6740772
Adj R2	0.0685	0.0663	0.0688	0.0669	0.0721	0.0687
Panel C	Modal Exit from District (=1)					
Major Terrorist Attack (1 lag)	0.0006*	0.0008	-0.0007	0.0012	0.0005	0.0007**
	(0.0003)	(0.0007)	(0.0006)	(0.0008)	(0.0015)	(0.0003)
Firm Industry Sample	All	Construction	Trade	Manufacturing	Transport	Other
Mean Outcome	0.0026	0.0027	0.0019	0.0024	0.0029	0.0027
Beta/Mean	0.2325	0.3225	-0.2521	0.4737	0.2014	0.2618
Observations	15417587	3013660	1829994	1964588	1868573	6740772
Adj R2	0.0686	0.0667	0.0689	0.0657	0.0704	0.0696

Notes: Observation is a firm-district-month. All regressions include month fixed effects, district-firm fixed effects, district-season fixed effects, and district linear and quadratic trends. Standard errors clustered at district level. *** p<0.01, ** p<0.05, * p<0.1.

Table B11: Firm Panel Activity After Major Terrorist Attacks

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Any calls made from district	Log Active Subscribers + 1			Log Active Districts + 1		
Major Terrorist Attack in Any District (1 lag)	0.258***	0.234***		0.320***	0.311***	
	(0.023)	(0.020)		(0.020)	(0.021)	
Major Terrorist Attack (Any) * Log Total Subscribers		0.008			0.003	
		(0.012)			(0.008)	
Major Terrorist Attack (Any) & Top Modal District (=1)			0.249***			0.305***
			(0.022)			(0.020)
Major Terrorist Attack (Any) & Other District (=1)			0.268***			0.337***
			(0.028)			(0.023)
Mean Outcome	1.787	1.787	1.787	1.821	1.821	1.821
Observations	54266	54266	54266	54266	54266	54266
Adjusted R2	0.880	0.880	0.880	0.808	0.808	0.808
Panel B: Employee based in district	Log Active Subscribers + 1			Log Active Districts + 1		
Major Terrorist Attack in Modal District (1 lag)	0.232***	0.211***		0.256***	0.241***	
	(0.023)	(0.020)		(0.019)	(0.021)	
Major Terrorist Attack (Modal) * Log Total Subscribers		0.007			0.005	
		(0.011)			(0.008)	
Major Terrorist Attack (Modal) & Top Modal District (=1)			0.215***			0.242***
			(0.020)			(0.019)
Major Terrorist Attack (Modal) & Other District (=1)			0.268***			0.285***
			(0.033)			(0.026)
Firm Size Sample	2+ Subscribers					
Mean Outcome	1.787	1.787	1.787	1.821	1.821	1.821
Observations	54266	54266	54266	54266	54266	54266
Adjusted R2	0.880	0.880	0.880	0.806	0.806	0.806

Notes: Observation is a firm-month. Dropping first six months of firm activity (when Top Modal District is measured) from panel. Major Terrorist Attack in Any District (1 lag) equals one if any subscriber for that firm was active in the previous month in a district experiencing a major violent event, and Major Terrorist Attack in Modal District (1 lag) equals one if any subscriber's modal location in the previous month was in a district experiencing a major violent event. Log Active Subscribers + 1 is the logarithm of one plus the number of subscribers making at least one call in that month. Log Active Districts +1 is the logarithm of one plus the number of unique districts in which subscribers make at least one call in that month. All regressions include month fixed effects and firm-season fixed effects. Standard errors clustered at firm level. *** p<0.01, ** p<0.05, * p<0.1.

C1 Kunduz Case Study Appendix

The "Fall of Kunduz" is one of the most significant events in the past decade of the Afghan conflict. On 28 September 2015, Taliban fighters overran Kunduz city, following a battle that had ebbed and flowed since the previous April in neighboring districts. This marked the first time since 2001 that the Taliban had captured a major city and signaled the continuing strength of the insurgency. Kunduz was retaken by the Afghan National Army (ANA) on 13 October, with support from U.S. ground and air forces. Since then, sporadic violence has continued in and around the city, and the Taliban made another concerted attempt to overtake Kunduz in October 2016.

C1.1 Qualitative Case Study

With a population of approximately 300,000 (about one-tenth the size of Kabul), Kunduz is the capital of Kunduz province, which borders Tajikistan in the North. Kunduz is primarily agricultural, with a complex irrigation network, but it has also served as a transit point for illicit drugs flowing toward Russia and then Europe. The province is ethnically diverse, home to Pashtuns, Uzbeks and Tajiks among others.

Kunduz has a long history of business activity. In the 1960s, it was home to one of Afghanistan's largest textile mills. During the 2000s, trade and services, along with manufacturing, provided an estimated one-third of household incomes (*Kunduz: Socio-Economic Profile*, n.d.). Kunduz also has a history of conflict, much of which revolves around a combination of land and ethnic disputes. Associated with this conflict has been a fragmentation of power, making it difficult for local authorities to defend the province and city.[31]

In an effort to stabilize Afghanistan following the collapse of the Taliban, a series of Provincial Reconstruction Teams (PRTs) were established around the country by the member-

[31] Kunduz was the first city to fall to the mujahidin in 1988 and then the first city in the north to fall to the Taliban in the 1990s. The Taliban were driven from the city by the mujahidin in November 2001 with the support of American forces participating in Operation Enduring Freedom (Devlin et al., 2009).

states of the International Security Assistance Force (ISAF).[32] At the same time, USAID established a development program in the region. Between 2002-2011, $125 million was provided for a wide range of programs, including in the area of business development. Indeed, USAID had an explicit objective in Kunduz to "create a developed business climate that enables private investment, job creation, and financial independence" (USAID, 2011).

During the early 2000s, however, conflicts between different ethnic groups continued to fester in Kunduz, as the Pashtuns argued they had been displaced from their land by Tajik-led forces (what constitutes an individual's land in Afghanistan remains contested given the weak property rights regime). According to one report, "the justice system in Kunduz is barely functioning and instead the local population prefers to use the informal justice system" (Devlin et al., 2009). Given this background, the Taliban have been able to maintain pressure on Kunduz despite the success of Operation Enduring Freedom in removing them from power.

The Taliban renewed their offensive on 24 April 2015 by striking at four districts outside Kunduz city. By the end of that week they controlled several major suburbs. In response, the Government of Afghanistan dispatched ANA forces, supported by U.S. fighter jets. But during the summer the Taliban continued to make gains around the city. On the morning of 28 September, Taliban troops routed the government troops that were holding the city. The following day, the ANA launched a counterattack with support from US special forces and airstrikes. Fierce fighting continued to October 13, with claims and counter-claims about who controlled the city. Finally, on 13 October the Taliban withdrew, citing "the prospect of additional casualties and ammunition expenditure" (Nordland, October 13, 2015).

[32] Germany was given responsibility for Kunduz in 2003, and 450 soldiers of the German Armed Forces were initially assigned to the region. By 2008 "around 570 German soldiers as well as about ten civilian staff – chiefly representatives of the Foreign Office (AA) and the Federal Ministry of the Interior (BMI) – were deployed in the PRT Kunduz" (VENRO, 2009).

C1.2 Empirical Analysis

We exploit the CDR data to demonstrate how subscribers from private firms, along with general mobile phone users, responded to the unexpected Taliban seizure of Kunduz in late-September and October 2015. In Figure C1a, we plot normalized call volumes for all towers in a 70 km radius of the Kunduz city center over a 24-week period centered on the takeover of the city on September 28 (marked by the black dashed line). We divide calling towers into two categories based on if the tower is located within a 10 km radius of the city center and thus covers urban areas (marked in green), or if the tower is located in a 10-70 km radius and thus covers rural areas and neighboring small cities (marked in orange).[33] The 10km radius approximates the boundaries of Kunduz district, which is the unit of geographical analysis below. We also divide callers based on if they are corporate lines subscribers (dashed line for "private"), or if they are part of the entire population of subscribers (solid line for "all"). These two categorizations result in four combinations, and we normalize each over the 24-weeks by subtracting the mean and dividing by the standard deviation for comparability.

Figure C1a shows a relatively smooth pre-trend in all four groups leading up to the seizure of Kunduz on September 28th, followed immediately by a sharp fall in the volume of calls originating from towers inside the city (green lines) and a corresponding spike in calls originating from towers outside the city (orange lines).[34] This effect lasts until the city is cleared in mid-October, and suggest some signs of persistence in that the level of activity inside the city returns to a level that is roughly 1 standard deviation lower in November and December 2015 than the previous levels in August and September. In Figures C4 and C5, we show placebo plots for calling activity over the same time period in four other provincial capitals: Kandahar and Lashkar Gah, both located in the more violent southern region of the country, and Hirat and Mazar, located in the west and northwest of the country closer to Kunduz. We do not find evidence of a similar response in any other city when Kunduz

[33] Figure C2 shows a map with the locations of towers in each radius.

[34] Figure C3 plots the daily locations of 150 corporate subscribers observed calling on the most days, demostrating their relocation from inside to outside the Kunduz city limits.

is seized. We do note a secular decline in the normalized activity of subscribers in Hirat and Mazar but note that is pattern precedes the attack on Kunduz and shows no evidence of sharp break in September 2015. By contrast, Appendix Figure C6 shows the long-term trend in activity in Kunduz was positive before September 2015 and flat afterward.

Returning to Figure C1a and comparing the dashed green line to the solid green line, we see evidence that corporate line subscribers responded to the September 2015 attack by leaving the city more quickly than regular users but also returned earlier. The same pattern reappears in Figure C1b with the October 2016 attack, suggesting that the behavior of corporate line subscribers may be a leading indicator of trends by all subscribers. The underlying mechanism for this effect is unclear, and might include more resources for travel, better information on the security situation, or higher risks of being targeted individually. Overall, this micro-level evidence of how one large security shock affects firm behavior measureable in CDR data motivates our analysis of the panel data.

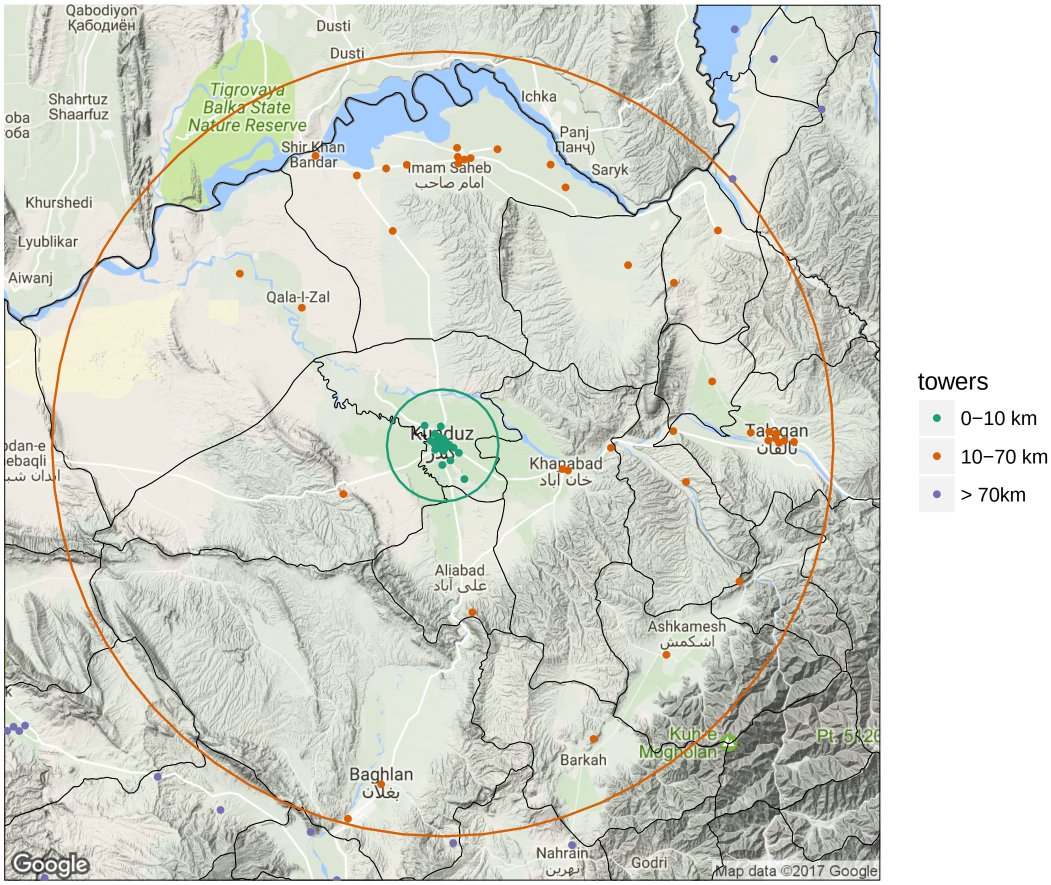
Figure C1: Mobile Phone Activity and the Fall of Kunduz (2015 & 2016)

(a) 2015

(b) 2016

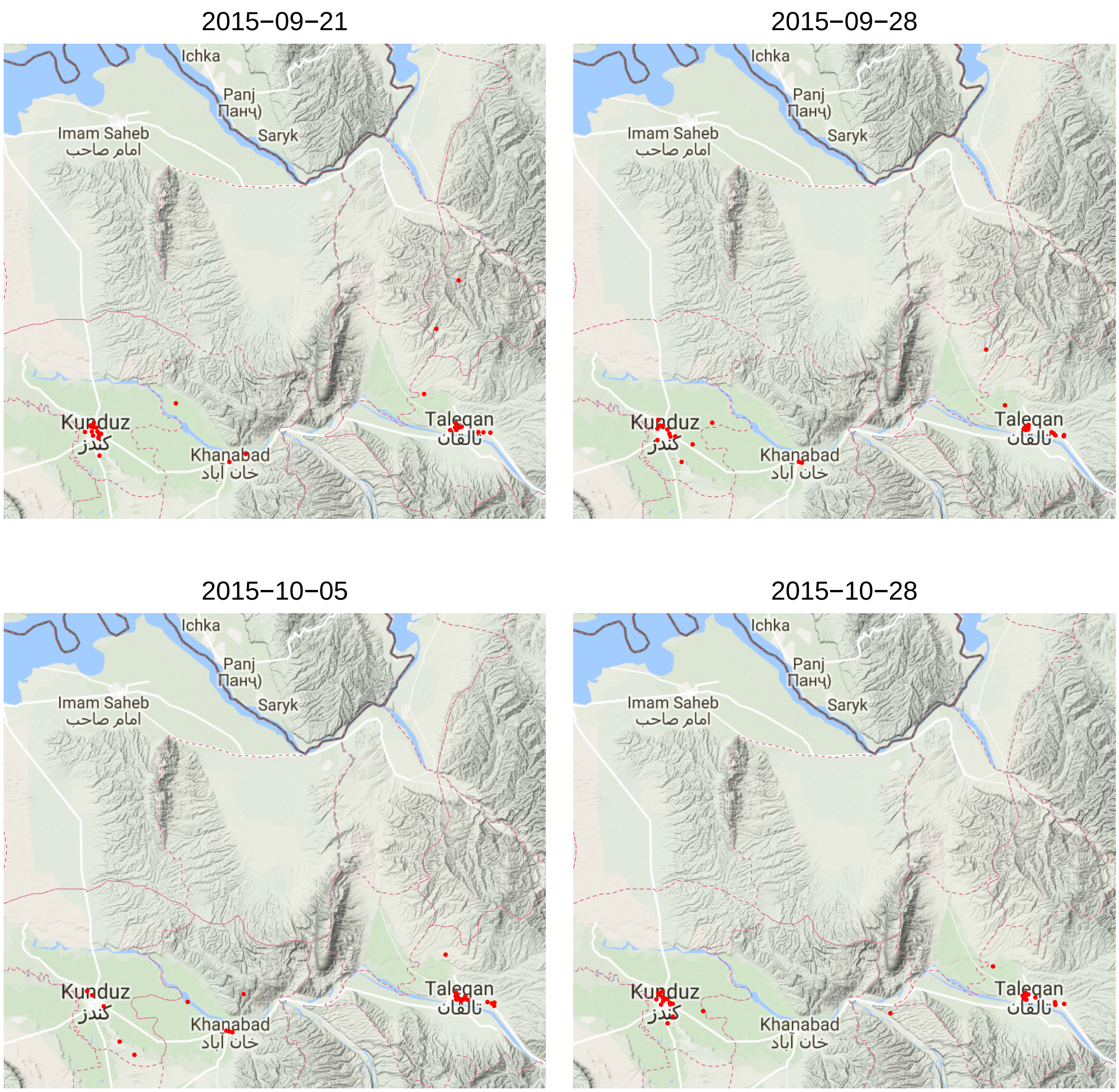
Notes: Panels show normalized mobile phone call volume by corporate subscribers (dashed lines) and all subscribers (solid lines) in the Kunduz region in 2015 (top panel) and 2016 (bottom panel). Green lines indicate calls from numbers within 10km of the city center; Orange lines indicate calls initiated from between 10km and 70km of the city center. Vertical dashed lines mark the dates of two Taliban attacks on Kunduz city (September 28, 2015 and October 3, 2016).

Figure C2: Mobile Tower Locations near Kunduz



Notes: Inner circle marks 10 km radius from Kunduz city center, and outer circle marks 70km radius from Kunduz city center. See text for details.

Figure C3: Daily Locations of Corporate Lines Subscribers - Kunduz 2015



Notes: Red dots represent daily locations of corporate line subscribers near Kunduz in 2015 calculated using CDR calling towers. Top left figure shows September 21, 2015, one week prior to the attack on the city. Top right figure shows September 28, 2015, the day of the attack. Bottom left figure shows October 5, 2015, one week after the attack and before it was cleared of insurgents. Bottom right figure shows October 28, 2015, one month after the attack on the city and after it had been cleared of insurgents. See text for details.

Figure C4: Placebo Tests: Calling Activity near Kandahar and Lashkar Gah (2015)

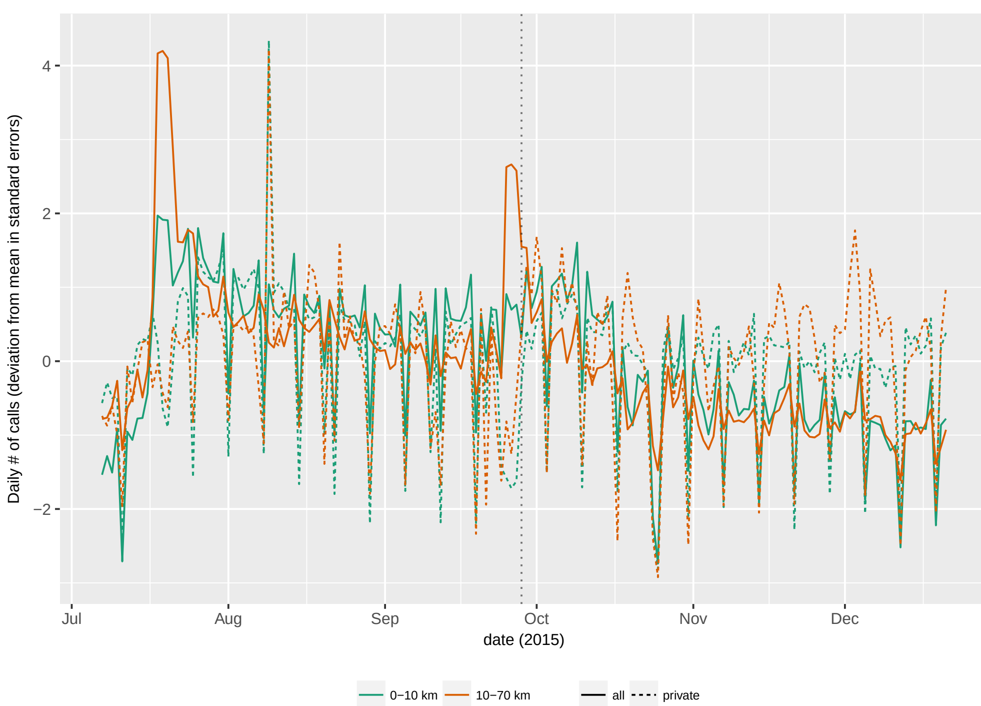
(a) Kandahar - 2015

(b) Lashkar Gah - 2015

Notes: Dashed black line in both panels marks date of September 28, 2015 attack in Kunduz city.

Figure C5: Placebo Tests: Calling Activity near Hirat and Mazar (2015)

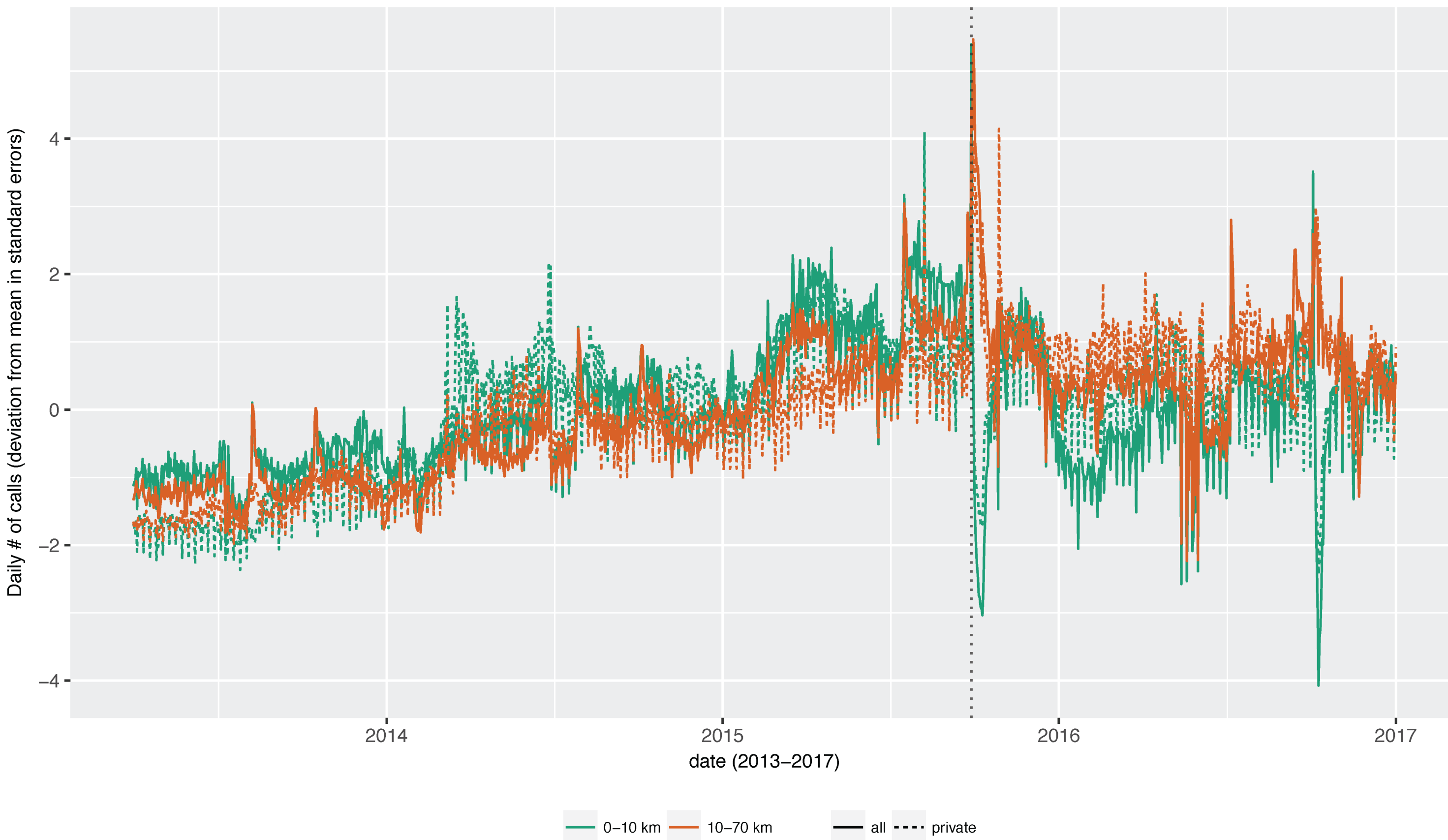
(a) Hirat - 2015



(b) Mazar - 2015

Notes: Dashed black line in both panels marks date of September 28, 2015 attack in Kunduz city.

Figure C6: Calling Activity Inside and Outside of Kunduz (2013-2016)



Notes: Dashed black line in both panels marks date of September 28, 2015 attack in Kunduz city.