Violence and Financial Decisions: Evidence from Mobile Money in Afghanistan*

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Abstract

We provide evidence that violence reduces the adoption and use of mobile money in three separate empirical settings in Afghanistan. First, we spatially merge nationwide administrative data on 96,000 violent events with the universe of mobile money transactions and find that users exposed to nearby violence reduce their mobile money account balances and conduct fewer transactions. Second, using high-frequency panel survey data from a field experiment, we find that subjects expecting violence are half as likely to respond to a randomized mobile money supply shock as those not expecting violence. Finally, analyzing financial survey data from nineteen of Afghanistan's 34 provinces, we find that individuals expecting violence hold more cash. Collectively, our evidence suggests that violence can impede the growth of formal financial systems.

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1 Introduction

Approximately 20% of the world's population lives in countries affected by fragility, violence or conflict (World Bank, 2011), and up to two-thirds of the world's extreme poor will soon be in these settings (Corral et al., 2020). While a substantial literature documents the positive relationship between conflict and poverty, investigations of the microeconomic mechanisms by which violence impedes economic development are more recent.[1] Such evidence indicates that conflict destroys capital (Davis and Weinstein, 2002; Miguel and Roland, 2011), deters investment (Besley and Mueller, 2012), changes economic decision-making (Voors et al., 2012; Callen et al., 2014; Brown et al., 2019), and introduces new uncertainty over the future.

This paper examines the relationship between violence and the adoption of mobile money in Afghanistan. We focus on this mechanism linking violence to economic development because mobile money holds particular promise for expanding financial access and thereby improving the lives of people, most of them poor, who do not use banks. Our main finding is that violence dampens the adoption and use of mobile money. This conclusion is supported by three sources of complementary empirical evidence.

The first set of results document how individuals exposed to nearby insurgent violence retain lower balances and are less likely to transact on their mobile money accounts. These results are based on analysis of the complete history of transactions made on Afghanistan's "M-Paisa" mobile money network over a 17-month period, which we spatially merge with a geocoded database of over 96,000 violent events recorded by international and Afghan forces. We find that M-Paisa users are less likely to use the mobile money system as a store of value or a means of exchange when exposed to violence. Even when using individual fixed-effects to control for unobserved and time-invariant heterogeneity, we find that the same individual is less likely to use mobile money in the immediate aftermath of violent events.

To better understand *why* violence might affect the adoption and use of mobile money, we

[1] Blattman and Miguel (2010) and Rohner and Thoenig (2020) review the economic causes and consequences of civil conflict.

conducted a field experiment in Afghanistan that created random variation in an individual's propensity to adopt mobile money. In the experiment, employees of a large, Afghan-staffed firm were randomly assigned to receive their monthly salary payments in mobile money or remain in the status quo cash payment system. Treated individuals paid via mobile money were significantly more likely to use mobile money as a store of value, even though they could easily withdraw their entire salary on payday. However, the treatment effect was heterogeneous by violence: whereas the average treatment effect of mobile salary payments increased account balances by roughly 7,000 AFs., employees expecting violence only increased balances by roughly half that amount.

Using high-frequency panel survey data from our experimental sample, we observe that the decrease in mobile money balance is accompanied by a comparable increase in cash on hand. This suggests that individuals exposed to violence prefer immediate liquidity over the other possible advantages afforded by mobile money. This relationship appears to be driven primarily by expectations of future violence: subjects who believe that future violence is more likely hold lower mobile money balances and keep more cash, even when facing similar objective levels of risk as proxied with strata controls. Importantly, these results are robust to using only within-individual variation in beliefs after including employee fixed effects.

We corroborate the importance of future expectations of violence with a nationwide household survey, collected for a separate study unrelated to the RCT. In this third independent empirical sample, we observe a strong positive correlation between an individual's subjective expectations of future violence and the amount they save in cash relative to other assets, even when controlling for local historical violence levels. By exploiting a rich set of covariates, we find evidence inconsistent with several possible alternative explanations, for instance that the correlations are driven by risk aversion, discounting factors or present bias.

In this way, the three empirical settings are meant to complement one another. The administrative records highlight, using comprehensive nationwide data, the dampening effect of violence on mobile money use. However, the data neither provide insight into allocations across the portfolio nor do they speak to mechanisms. The field experiment provides panel survey data attempting to capture activity across participants' entire financial portfolio, and so allows us to check for substitution into cash when mobile money balances go down. The third empirical exercise, which uses a large cross-sectional survey that includes data on individual decision parameters, helps shed light on potential mechanisms linking violence to savings.

While the three empirical exercises are complementary, we acknowledge that no single approach offers watertight causal identification. The analysis of large-scale administrative data relies on the identifying assumption that the precise timing of when an individual is exposed to violence in the period covered by our data is random, conditional on that individual's general exposure to violence (individual fixed-effects), and the dynamics of the local environment (which we approximate with time fixed-effects and regional time trends). We believe this is plausible in our setting since the timing of insurgent violence is inherently secretive and relies heavily on the element of surprise. On the other hand, because violence is endemic in Afghanistan, and most of the individuals will have experienced violence before the period we observe, this also means that our estimates, under the identifying assumption, correspond to the effect of directly experiencing violence after having had some prior exposure.[2] The second exercise examines heterogeneous responses to a randomized mobile money supply shock, and thus is not causal. The third exercise relies on cross-sectional data, and so can only be interpreted as correlational. As the first and second exercises examine populations enrolled on the mobile money platform, those estimates should be considered as representative of mobile money users, not the full Afghan population. Still, the picture that emerges from these three independent analyses suggests a common underlying economic response to violence.

The evidence in this paper thus indicates that individuals experiencing – and expecting – violence in Afghanistan appear to prefer cash to mobile money. The vast majority of Afghans

[2]We note that we test our main results controlling for previous exposure *within* our sample period and our results remain robust.

do not use formal financial systems: only 15% of Afghan adults hold bank accounts and only 4% save money at a financial institution (Demirguc-Kunt et al., 2018).[3] The development of financial systems requires broad participation and long time horizons from account holders. This may be particularly true for mobile money, a technology with network externalities in adoption and use (Mas and Radcliffe, 2011). Inspired in part by the success of mobile money in Kenya, advocates point to the opportunity to build a new financial system with mobile money that requires less investment into a brick-and-mortar bank-based financial system (Dermish et al., 2011; Mbiti and Weil, 2015; Suri et al., 2012). Our results suggest, however, that individuals may be reluctant to use mobile money if violence and instability remain part of their daily lives.

We interpret our evidence using a framework, developed in Section 3, that emphasizes two key properties of mobile money relative to cash that plausibly vary with levels of violence. The framework predicts that as violence increases financial decision-makers will reduce mobile money savings because it will be less liquid than cash, eventually outweighing any benefits, including that it may be harder to steal. We posit that the practical reason mobile money becomes less liquid when violence increases is that mobile money agents may be less willing to operate in contested territory. This observation contrasts with policy enthusiasm for how mobile money might leapfrog traditional financial institutions in fragile settings like Afghanistan, as financial decision-makers may prefer the less secure but more liquid alternative of cash.

Our findings complement a growing body of literature documenting the generally positive effects of the proliferation of mobile phones and mobile money in developing countries (Aker and Mbiti, 2010). Early work by Jensen (2007) and Aker (2010) showed how mobile phones increased the efficiency of agricultural markets. Subsequent work by Jack and Suri (2014) and Blumenstock et al. (2016) linked mobile money use to more efficient risk sharing, and Suri

[3] Aghabarari et al. (2018) use survey data to document that Afghan households facing income uncertainty accumulate precautionary wealth reserves using livestock in low-conflict areas and gold and silver in high-conflict areas, but lack detailed data on formal financial portfolios of the type analyzed here.

and Jack (2016) documented the potential for mobile money to reduce poverty, particularly among women. Field experiments in Afghanistan and Niger suggest that mobile-linked salary payments can create efficiencies for employees, firms and governments (Blumenstock et al., 2015, 2018; Aker et al., 2016). Relative to this work, our results suggest how violence and conflict might limit such benefits by reducing mobile money uptake and use.

The paper also relates to a substantial behavioral literature on the potential malleability of decision parameters (cf. Malmendier and Nagel, 2011; Beine et al., 2020; Cameron and Shah, 2015; Cassar et al., 2017; Chantarat et al., 2019; Hanaoka et al., 2018; Voors et al., 2012).[4] Our data do not allow us to conclusively identify why violence changes financial decisions, or why those experiencing violence appear to prefer cash. It could be because it is much more liquid, because it is more familiar, and has never been the subject of a dramatic public failure, unlike the banking system. Mobile money, and indeed formal financial institutions of any sort, are still not widely used in Afghanistan. Such an interpretation is consistent with the result in Callen et al. (2014) that individuals prefer options that are completely safe when reminded of the extreme uncertainty that characterizes much of life in Afghanistan. However, the relationship between mobile money use and violence may be different in countries where adoption is widespread or criminality is a greater concern than the insurgent violence we study, possibly because mobile money is harder to steal.

The remainder of the paper is structured as follows. The next section reviews the setting and provides institutional details. Section 3 provides a simple framework that characterizes how violence can shape the decision to use mobile money. Section 4 provides initial evidence on the relationship between violence and mobile money transactions from two large administrative datasets from Afghanistan during 2010-2012. Section 5 presents further evidence from the randomized experiment conducted in Afghanistan during 2012-2013. Section 6 provides additional evidence from a nationwide household survey conducted in December 2010, and Section 7 concludes.

[4] Chuang and Schechter (2015) provide a comprehensive overview of this literature.

2 Violence and Financial Development in Afghanistan

2.1 Violence in Afghanistan

Afghanistan is poor and severely affected by conflict. Beginning with a communist coup in 1978 and the Soviet invasion in 1979, the country has endured forty years of nearly continuous civil war. After US and NATO military forces began operations to defeat the Taliban regime in October 2001, the new Afghan government worked with international aid donors to make significant progress in increasing primary school enrollment, reducing child and maternal mortality, and increasing income per capita. But ever since the Taliban insurgency gained strength starting in 2006, the civilian population's exposure to violence has continued to be a major issue. From 2009 to 2019, the United Nations documented 100,000 civilian casualties, with more than 35,000 killed and 65,000 injured (United Nations 2020).[5] As shown in Figure 1a, violence during 2010-2012, the period covered by our data, was spread across the country but particularly concentrated in the south and east of the country along the border with Pakistan where the insurgency is based. At the time of writing, the Taliban rapidly consolidated control of the country, as American military forces exited, concluding the military engagement that began in 2001.

2.2 Financial Development in Afghanistan

Afghanistan's number of commercial bank branches per 100,000 adults is approximately 1.9, which is less than a fifth of the South Asia regional average of 10.4 (IMF, 2019). Bank branches are typically limited to major urban centers, such as provincial capitals, and rarely operate in more remote areas of the country. The 2010 collapse of Kabul Bank, one of the country's largest financial institutions and the primary vehicle used to pay several hundred thousand Afghan government salaries each month, further shook confidence in the formal

[5]In 2012, the United Nations recorded over 2,750 civilian deaths, with approximately 80% of casualties attributed to the insurgency (United Nations 2013).

financial system (Filkins, 2011). With only 4% of Afghans saving with a formal bank account, most rely on cash holdings and other informal savings vehicles (Demirguc-Kunt et al., 2018). The money exchange network of hawala brokers offers a parallel system for domestic and international payments, with limited functionality for long-term savings, but data on its size and scope in Afghanistan is limited by its informal nature (Maimbo, 2003).

2.3 Mobile Money in Afghanistan

Mobile phone ownership in Afghanistan grew rapidly over the decade preceding the study period, from approximately 25,000 subscribers in 2002 to over 18 million subscribers in 2012 (World Bank 2020). Roshan, the largest Afghan telecommunications operator, developed its M-Paisa mobile money platform in late-2008 with the British multinational Vodafone, and now boasts over 1.2 million M-Paisa subscribers, though the number of active users is far smaller.[6] The M-Paisa system was initially focused on micro-loan repayments, but it soon expanded to include peer-to-peer transfers and airtime purchases. Starting in 2009, M-Paisa expanded into the mobile salary payment space as the Government of the Islamic Republic of Afghanistan began a pilot project to pay Afghan National Police officers through the system, and Roshan began paying its own national employees via M-Paisa. Similar contracts to provide mobile cash transfers to beneficiaries of humanitarian assistance soon followed.

While the M-Paisa platform can be accessed anywhere that Roshan cell coverage is available, in-person deposits, withdrawals and purchases require the presence of registered mobile money agents. These agents function as "human ATMs," providing deposit and withdrawal services to individual users interested in converting either their cash holdings into mobile money or vice-versa. The study period marked a concentrated effort by Roshan to significantly expand agent coverage outside of Kabul to include other major population

[6] Four major mobile operators compete in Afghanistan: Afghan Wireless Communications Company (AWCC), Etisalat, Mobile Telephone Network (MTN), and Roshan. In addition, two minor operators are in the market: Afghan Telecom and Wasel Telecom, with each covering less than 3% of the market. In 2012, Roshan had an estimated subscriber base of over 5.6 million and an estimated market share of 32%, with coverage in all 34 provincial capitals and 230 of Afghanistan's 398 districts (Hamdard, 2012).

centers such as Herat, Mazar, Jalalabad, Helmand and Kandahar. Roshan also continued to recruit agents in rural areas to service specific populations, such as recipients of mobile salary payments or humanitarian assistance. Roshan faced considerable challenges recruiting agents to work in remote and insecure locations. In 2013, a USAID-funded market research study found that the typical Afghan mobile money user had been enrolled by their employer: of a nationally representative sample of 1,070 SIM owners interviewed, 5% reported using mobile money – 6% male and 4% female, and equal proportions of urban and rural respondents (Altai, 2013). After the time period covered by our data, several of Roshan's competitors launched their own mobile money services.

As a 2011 market assessment noted, mobile money in Afghanistan faces "the challenge of delivering services in a landscape with low levels of trust in formal institutions to consumers with highly variable degrees of textual, financial and technological literacy" (Chipchase et al., 2011). While M-Paisa enjoyed certain clear advantages of cost, time and privacy relative to alternative financial transfer options such as banks, hawala or in-person exchange, potential users also cited common concerns about penetration, accessibility and perceived risk as deterring adoption.[7] At the same time, brand recognition and public trust in major mobile operators such as Roshan were among the highest of any firms in Afghanistan. Government regulations in Afghanistan require mobile operators without a banking license to maintain deposits in local banks equal to the entire value held on their mobile money system, creating a significant connection between mobile money users and the existing financial system.

2.4 Mobile Salary Payments

Given widespread adoption of mobile phones, mobile money provides a promising alternative to bank or cash transfers for moving funds across large distances at low cost using a simple SMS technology. In the particular case of mobile salary payments - wage transfers made by

[7] Various financial systems also complement each other. For instance, customer-facing M-Paisa agents often receive cash liquidity from "super-agents" such as local banks in urban areas and hawaladars in more remote or insecure districts.

an employer to an employee using mobile money - large firms are able to instantaneously complete individual financial transfers to their employees. Individual users are notified of a transfer into their account by SMS message, and can check their balance and complete other functions using a simple interface that does not require smart-phone technology. For the firm, mobile salary payments offer a means to address concerns around physical security, logistics and corruption associated with cash salary payments by effectively outsourcing cash management to the mobile operator's network of mobile money agents. Individual users can maintain a balance on their mobile money account, providing a means of storing value.[8] Individual users can also use the mobile money platform as a means of exchange: to purchase pre-paid airtime directly from their mobile operator, to send and receive mobile money with other mobile subscribers in the same country (either on the same mobile network or on a competitor's network), and to receive remittance transfers from outside their country through partnerships with firms such as Western Union.[9]

3 Conceptual Framework

Mobile money's usefulness as a store of value relates to violence in at least two key ways. First, mobile money is less liquid than cash in violent and contested areas, in part because mobile money agents are less likely to operate in such environments. For instance, in data collected for a separate project, we find that travel times to cash out mobile money salaries are 37% longer in districts controlled or contested by the Taliban, relative to those under government control. Second, while mobile money is much less liquid, a widely cited benefit of mobile money is that it is also more challenging to steal because a password is required to convert it to cash (Beck et al., 2018; Suri et al., 2021; Aron and Muellbauer, 2018).[10]

[8] As in the case of Afghanistan, local regulations may restrict the payment of interest on mobile money accounts not linked to a bank account, and also impose maximum balance limits on mobile money accounts.

[9] While deposits and airtime purchases are costless on Roshan's M-Paisa platform, other mobile money transactions such as withdrawals and peer-to-peer transfers involve a graduated tariff structure. The mobile salary payments product includes the cost of one withdrawal each month.

[10] To the extent that local violence might influence general perceptions of stability, it could also influence beliefs that mobile money systems will continue to operate at all.

Therefore, it might provide a more useful way to save in areas where the rule of law has broken down.

This section provides a simple framework that characterizes how violence can shape the decision to use a formal financial technology, in this case mobile money, by focusing on these two features. It assumes – consistent with the reality on the ground – that mobile money will be less *liquid* where there is more violence, but that it will be *safer*. The model further posits that eventually the illiquidity of mobile money in the face of violence will outweigh the benefits from increased safety. Whether this is true in actual fact is an empirical matter, and is the focus of the rest of the paper.

We model the decision to hold cash using a two-period approach. An individual is considering how to store wealth w, which can be held either as cash, which offers no return, or in mobile money, which offers a random rate of return $\tilde{R}$, which can be either positive or negative. a is the amount kept in mobile money, and $w - a$ is the amount kept as cash. Decisions are made in period one, and returns are realized in period two.

Period two wealth is then:

$$\tilde{w} = a(1 + \tilde{R}) + (w - a) \tag{1}$$

The expected utility of holding a in mobile money is therefore $u(a) = E(w + a\tilde{R})$.

A standard result gives that, for strictly risk averse agents, $a = 0$ if and only if $E\tilde{R} < 0$. In other words, those who are risk averse will choose to hold a zero mobile money balance if and only if the expected return to doing so is negative.

We model randomness in the rate of return, $\tilde{R}$, as coming from violence through two channels. First, mobile money is less liquid than cash, depending on the availability of agents and the difficulty accessing them. We therefore assume individuals lose a share of their wealth equal to $L(v)$ in order to find a mobile money agent and convert their mobile money to cash. This, in turn, is a function of violence, which is a random variable v, where

$L'(v) > 0$. Second, mobile money is less subject to appropriation than cash. Individuals therefore receive a positive return for a given realization of violence $S(\tilde{v})$, where $S'(v) \geq 0$.[11] The rate of return, therefore, is $\tilde{R} = S(\tilde{v}) - L(\tilde{v})$.

We assume further that at low levels of violence $S(v) > L(v)$; i.e., that individuals in non-violent areas hold some positive amount of mobile money — a finding that is consistent with our data. If $L'(v) > S'(v)$, such that the liquidity cost of mobile money increases faster than the safety benefit, then it follows that $\exists v*$ such that $S(v) - L(v) < 0$ and people will switch to holding no mobile money. Correspondingly, as individuals' expectations of violence increase, their beliefs about the relative return to mobile money will decrease.[12]

This conceptual framework suggests two empirical regularities that are the twin foci of our analysis: First, that local exposure to violence correlates negatively with mobile money use (a pattern we explore in large-scale administrative data on mobile money use); and second, that there is a corresponding substitution into cash (something we investigate using experimental and survey data). Our data cannot, however, speak more than suggestively to the precise mechanisms behind these trends. However, the fundamental dynamic, whereby cash is *perceived* to be more useful in contested, rural areas, is the key empirical question of concern. We focus our model on these two channels because our descriptive data and first-hand observations from Afghanistan strongly suggest that the main considerations affecting the usefulness of mobile money in relation to violence are the availability of agents, the potential safety that mobile money offers relative to cash, and the possibility that experiencing violence may influence people's beliefs about the tradeoffs between the two. This highlights a fundamental challenge to mobile money adoption in contested, rural areas: breakdown in the rule of law means that agents cannot operate safely (making mobile money

[11]Strictly, $S(v)$ is positive only in the sense that less money is potentially extorted than if cash were held. However, without loss of generality, we assume that the cost of holding cash is zero.

[12]This framework could be generalized in several ways. For instance, if violence generates a direct preference for certainty, as documented in Callen et al. (2014), then the expected level of violence $v*$ at which the return to holding mobile money is positive would be even lower. In this case, increasing subjective beliefs about the future probability of violence would not only reduce its perceived relative return, but it would also make individuals directly prefer the asset that is less exposed to risk.

fundamentally illiquid), and so potential mobile money adopters need to recalibrate their decisions as stability deteriorates.

4 Violence and Mobile Money: Administrative Data

Our primary focus is on understanding the effect of violence on financial decision-making in Afghanistan. We begin by providing evidence that exposure to nearby violence decreases the likelihood that an individual will use, and store balance in, a mobile money account. To do this, we create a novel dataset that combines the complete history of M-Paisa transactions over the period from December 2010-April 2012 with records of all violent incidents recorded by international forces in Afghanistan. We obtain the M-Paisa data from Afghanistan's primary mobile phone operator, Roshan Telecom. These data contain the complete anonymized and geo-tagged mobile phone call records of each M-Paisa user, which we then use to approximate the location of each individual user on every day for which we have data.

Violence data are obtained from time-stamped and georeferenced records collected by Afghan and International Security Assistance (ISAF) forces. The data include, among other things, time (by the hour), geolocation (within meters), and the type of incident (e.g., direct fire, Improvised Explosive Device (IED)).[13] In all, the combination of the M-Paisa transactions data with the violence data allows us to determine each M-Paisa subscriber's exposure to violence over time. The resultant dataset captures roughly 630,000 M-Paisa transactions by 24,279 unique subscribers, and incorporates information on more than 96,000 violent events and roughly 3.5 million geolocated and timestamped mobile phone records.

Using methods described in greater detail in Appendix A, we create a panel of data that captures, for each individual i in each time period t, several measures of M-Paisa use, which we denote by Y_{it}. The mobile phone records are then used to determine each individual's "Center of Gravity", denoted as COG_{it}. This is a weighted centroid of the locations from

[13]We thank Andrew Shaver and Austin Wright for providing these data. Refer to Condra et al. (2018) for a more detailed description of this dataset.

which we observe the user originate phone calls, which provides an approximate location for each individual in each time period. Figure 1b plots the location centroids for all individuals within our sample period. Finally, we measure each individual's exposure to violence $Violence_{it}$ by assigning each known violent incident v_{lt} at location l at each time t to each individual who is within a fixed radius R of the incident, i.e.:

$$Violence_{it} = \sum_{v_{lt}} \left[distance(COG_{it}, v_{lt}) \leq R \right]$$

Our main results measure the effect of i being exposed to any violent event at time t, using a binary treatment variable that takes the value 1 if $Violence_{it} \geq 1$ and 0 otherwise. We also present results disaggregating the violence measure into the three most common types of violence observed: direct fire attacks, indirect fire attacks, and IED explosions. Direct fire refers to attacks on a target that is visible to the attacker. Examples include small arms fire, rocket propelled grenades, or hand grenades. Indirect fire refers to attacks where the attacker fires from a distance beyond line-of-sight and includes artillery, mortars and rockets. Indirect fire and IED explosions are typically more indiscriminate and thus may be more consequential to civilian bystanders than more targeted direct fire attacks.

We estimate the relationship between violence and M-Paisa use with a regression model that includes individual fixed-effects π_i, time fixed-effects μ_t, and district-specific linear time trends η_d.[14]

$$Y_{it} = \beta_0 * Violence_{it} + \pi_i + \mu_t + \eta_d t + \epsilon_{it} \tag{2}$$

The results we present below use a specification that attaches each violent incident to any individual within a 10-kilometer radius, i.e. $R = 10$. To address potential data sparsity related to individual locations, we aggregate violence exposure to the monthly level by using the maximum value of $Violence_{it}$ over all days in a given month. Similarly, we average daily M-Paisa balances and other M-Paisa transaction types at the monthly level, which is the

[14]District time trends $\eta_d t$ are given by the continuous time variable interacted with district dummies.

typical time frame for cycles of salary payments and withdrawals. We will further focus our attention on: (i) users who have at least two days of recorded activity on the M-Paisa platform - allowing us to ignore short term users who are automatically enrolled or who use the platform very briefly, and (ii) users who receive salary payments via the platform, as we observe limited evidence of deposits and peer-to-peer transfers in the general population of users. These restrictions limit our sample to a total of 7,551 individual salary users during the period from December 2010 to April 2012.

With this specification, unobserved time-varying individual characteristics (that are not common across all individuals and that deviate from region-specific trends) could bias our estimates in unforeseen ways. In particular, the key identifying assumption of model (2) is that the precise timing of when an individual experiences violence is random, conditional on time-invariant properties of the individual (captured by the individual fixed-effects π_i), seasonal characteristics that are common across all individuals in a given month (the time fixed-effects μ_t), and regional trends in violence and mobile money use (the district-specific linear time trends $\eta_d t$). We think this assumption is reasonable in Afghanistan, where the timing of insurgent attacks is meant to surprise government forces.[15] However, it is possible that individuals on the ground would be better able to predict idiosyncratic violence than our econometric model; we return to this point below.

4.1 Administrative Data Results

Table 1 presents the results from the fixed-effects specification in Equation (2). Overall, we document a robust negative relationship between violence exposure and M-Paisa usage. On average, individuals exposed to violence significantly reduce their M-Paisa balance during

[15] We also perform several econometric tests to assess whether violence can be predicted beyond what is captured by our econometric specification. Specifically, Appendix Table A0 assesses whether residualized violence can be explained using recent trends in violence and M-Paisa use, where residualized violence ξ_{it} is obtained by regressing violence on the fixed effects in Equation (2), i.e., $Violence_{it} = \pi_i + \mu_t + \eta_d t + \xi_{it}$. Using a basic linear model as well as a machine learning approach (i.e., a regression tree with 10-fold cross validation), we find that characteristics such as lags and trends in violence and M-Paisa balance are consistently unable ($R^2 \leq 0.035$) to predict residualized violence.

periods of heightened violence (column 1). More precisely, exposure to violence is associated with a decrease in a user's average M-Paisa balance of 134 Afghanis (approximately $2 USD) (panel A). This represents about a 6% drop in the mean value of the dependent variable. When violence exposure is disaggregated by violent event type (panel B), we uncover large and statistically significant effects on M-Paisa balance of exposure to indirect fire and IED explosions. Specifically, exposure to an indirect fire event or an IED explosion decreases average M-Paisa balance by 356 (15% drop relative to mean value) and 263 (11% relative to mean value) Afghanis, respectively. We note that while the effect of indirect fire attacks and IEDs is large and significant, the effect of direct fire attacks on M-Paisa balance is not. This pattern is consistent with the indiscriminate nature of indirect fire and IED events, which could make them plausibly more consequential to the behavior of civilian populations.

Column 2 of Table 1 indicates violence has similar effects on the frequency of M-Paisa use: violence exposure is associated with about a 24% reduction in the average number of transactions.[16] Columns 3-5 show results for the most common M-Paisa transaction types. We find that violence exposure leads to a negative and significant drop in the average number of withdrawals (column 3), deposits (column 4), and peer-to-peer transfers (column 5).[17]

As discussed above, an important stylized fact in Afghanistan is that violence is quite common, and most individuals in our sample have likely been exposed to violence prior to our period of study. This can be seen in Figure 2a, which plots observed monthly exposure to violence for the users in our sample using a 10-kilometer radius. The high frequency of violence exposure limits our ability to use an event-study framework to measure the impact of violence. It also implies that our results should be interpreted as measuring the impact of

[16] Relative to a baseline average of 0.196 transactions per month.

[17] In Appendix Table A1, our estimates are also similar when we include non-mobile salary users in the sample. In Appendix Table A2, we show that estimates of the effect of violence are similar to Table 1 when we define the impacted region as within 5 km or between 5-10 km from the location of the violent event. In Appendix Table A3, we calculate an individual's estimated location using the location of the village closest to the Center of Gravity, using information on village locations obtained from the Central Statistics Organization (CSO) village location dataset. This robustness helps ensure that the estimated location is a populated area. Our results using this alternative measure are almost identical to our main results using the Center of Gravity. Appendix Figure A1 maps the daily estimated locations using the village closest to the estimated Center of Gravity.

current exposure to violence relative to an unknown degree of prior exposure. In addition, we show that our results do not change significantly after controlling for past exposure to violence measured during our sample period.[18] Although we cannot condition on exposure prior to our period of study, this exercise shows that the impact of contemporaneous exposure to violence remains significant even after controlling for recent past exposure.

A key advantage of our data is that we can exploit its panel structure to account for time-invariant individual characteristics. Appendix Table A5 highlights how these time-invariant characteristics might otherwise bias our results by presenting variants of Equation 2 with and without different fixed effects. When analyzing M-Paisa balance, the specification without any fixed effects (column 1) indicates a negative correlation between violence exposure and M-Paisa balance. However, we expect this estimate to be downward biased, since people who more regularly experience violence are likely different (and less likely to use mobile money) than those who are more physically secure. This bias is evident as increasingly restrictive fixed effects are added from columns 1 to 4. A similar, and more stark, pattern exists when analyzing M-Paisa transactions: while the cross-sectional analysis (column 5) suggests a positive correlation between exposure to violence and M-Paisa transactions, the effect changes sign once we account for trends in M-Paisa transactions and district characteristics (columns 7 and 8).

While the administrative data from the phone company contains rich information on mobile money transactions, and the panel structure allows us to use fixed effects to control for time-invariant individual factors, they do not contain any other information about the subscribers (demographics, income, etc.). Thus, we cannot easily control for time-varying individual factors in our regressions. Instead, as an additional test of the robustness of the results in Table 1, we control for time-varying district characteristics using a quarterly survey sponsored by the International Security Assistance Forces in Afghanistan (Condra et al., 2019). Using the Afghanistan Nationwide Quarterly Assessment Research (ANQAR) survey,

[18] Specifically, we estimate Equation (2) adding a control for the total number of violent events within a 10-kilometer radius up to $t-1$. These results are presented in Appendix Table A4.

we control for the following variables at the district-month level: average age; share of female population; share of rural population; share of population with primary, and secondary education; share of population receiving income from farming; average number of hours per day with electricity; and the share of the population that is Pashtun.[19] Appendix Table A6 compares the estimated relationship between violence exposure and M-Paisa usage with and without the ANQAR controls, estimated on the sample from Table 1 that overlaps with the ANQAR data. Comparing Panel A with Panel C and Panel B with Panel D, our estimates are not substantively changed by including these covariates in the specification.

5 Violence and Mobile Money: Experimental Results

The results above provide strong evidence that exposure to violence is associated with reduced use of Afghanistan's mobile money system, even when controlling for time-invariant unobserved heterogeneity at the individual level. However, a causal interpretation of these results is difficult, since we are unable to control for time-varying unobserved heterogeneity that may explain why users join the mobile money platform. Moreover, the administrative data provides limited insight into the mechanisms driving individual decisions to reduce M-Paisa usage.

To address these concerns, we conducted a randomized controlled trial that created random variation in an individual's propensity to adopt mobile money. The experiment was conducted in partnership with a large firm operating in some of the most violent areas of Afghanistan. The firm had decided to switch their salary distribution platform to use mobile money payments instead of cash payments. We partnered with them to conduct an evaluation of this transition, using a staggered roll-out design that randomly assigned the date on which each employee would make the transition from cash to mobile

[19] The primary purpose of the ANQAR survey is to track general attitudes and beliefs among the Afghan population – see Data Appendix A.1.4 for details. ANQAR is a repeated cross-section survey that is highly regarded by Afghan survey research experts. Our specifications control for the main time-varying covariates available in ANQAR.

money. We combine administrative transaction records with monthly survey data on both the treatment and control group to develop a more nuanced understanding of the factors driving individual decisions to reduce usage of M-Paisa. Blumenstock et al. (2015) reports this field experiment's results on mobile money adoption, employee welfare and firm cost-savings, but does not analyze the relationship between mobile money usage and violence.

5.1 Experimental Protocol

The partner firm was the Central Asia Development Group (CADG), a private contractor implementing the USAID-funded Community Development Program (CDP) in the conflict-affected southern and eastern provinces of the country.[20] In 2011, several CADG staff in Kabul and Kandahar entered a pilot of Roshan's mobile salary payment program. Based on the results of the pilot, in mid-2012 CADG made the decision to transition all of their employees in the CDP program from cash to mobile salary payments. However, CADG did not want to transition all employees at the same time, and instead planned to implement the change over the course of several months.

After discussing their plans with our team, CADG agreed to randomize the dates on which employees were enrolled in mobile salary payments. We note that our research team's involvement did not affect CADG's decision to switch their CDP employees from cash to mobile money; that decision was made prior to our team's involvement, presumably because of the cost savings and logistical advantages offered by mobile salary payments. Our research team's involvement was focused on evaluating the impact of this transition – including both potential positive and negative impacts to employees – as CADG was interested in gathering rigorous evidence on how their employees would be affected by the transition to mobile money. Such information could be useful to CADG for a range of reasons, including future

[20]CDP's primary objective is to provide labor-intensive community development projects to reduce the impact of economic vulnerability and increase support for the Government of the Islamic Republic of Afghanistan. The projects undertaken by the communities involved reconstructing municipal infrastructure, irrigation systems and valued public facilities such as schools and clinics. CDP's main beneficiaries are at-risk populations including unemployed men of combat age, internally displaced persons, those suffering from extreme poverty and other marginalized segments of Afghan society.

development work under separate contracts.

In July 2012, CADG's Community Development Program (CDP) employed approximately three hundred seventy-five (375) employees based in eight offices located in the capital Kabul and in the southern and eastern provinces of Afghanistan. The RCT was launched in August 2012 with 341 CDP employees operating in seven provinces: Ghazni, Helmand, Kabul, Kandahar, Khost, Paktia and Paktika (see Appendix Figure A2).[21] Throughout the analysis that follows, we trim the top .5% of outliers in M-Paisa balances, which results in discarding one extreme outlier observation in the treatment group with an average M-Paisa balance 10 standard deviations above the mean, leaving a final sample of 340 employees.[22] The experimental sample included all CDP employees who worked in office locations with Roshan mobile coverage, and excluded CDP security staff who were paid through an alternative system.

Half of the employees in the experiment were randomly assigned to the mobile salary system, while the other half were paid by CADG's existing cash-based system to provide a valid comparison group during the study period. Employees in the control group receive a basket of interventions that closely resembled those received by the employees in the treatment group.[23] The key difference between treatment and control groups is that members of the treatment group had their salary distributed via the M-Paisa mobile money service, while members of the control group continued to be paid in cash by their employer.

In addition to stratifying treatment within each province, the randomization protocol

[21] Employees in Zabul province could not be included due to a lack of reliable mobile coverage on the Roshan network in their area.

[22] We also consistently present results trimming the top .5% of outliers in self-reported cash savings in order to address a handful of extreme values that appear to be enumerator data collection errors.

[23] Both sets of employees received a group training on the use of the M-Paisa mobile money system, including how to send, receive, deposit and withdraw funds, as well as how to purchase mobile airtime using mobile money. Both sets of employees were given new phones, identified as their new official work phones, and both sets of employees were given Roshan SIM cards, identified as their personal property. As all phone usage is pre-paid, employees were encouraged to use these new phones and SIMs for their personal calls as well, and they are instructed not to remove the Roshan SIMs and replace them with other network SIMs. Finally, both sets of employees were individually registered for the M-Paisa service, which due to "know-your-customer" regulations requires the recording of biographical information and copies of photos and a national ID card.

included two further blocking variables: the share of monthly income transferred to a family, and the level of monthly expenditure on phone airtime.[24] While employees in five provinces are able to withdraw their mobile salary funds by visiting a mobile money agent (typically a teller at a local bank branch or a local merchant with significant turnover to enable regular liquidity), employees in Paktia and Paktika received regular in-person visits from an agent to their office in order to address security concerns specific to those two provinces.[25]

To address the logistical challenges of registration team travel within Afghanistan, treatment followed a staggered rollout plan in which Kabul employees received the intervention in July 2012, followed by employees in Paktia and Paktika in August 2012, employees in Ghazni and Khost in September 2012, and employees in Helmand and Kandahar in October 2012. Before each group received new phones, training and M-Paisa registration (or notification of their treatment status), a first wave of face-to-face interviews took place to collect more detailed baseline information. Following the in-person baseline, monthly phone surveys were conducted with employees at all sites. A second wave of face-to-face endline surveys took place at each province based on availability.[26]

The randomization assignment protocol was implemented with 100% compliance, meaning all 171 employees assigned to receive mobile salaries were in fact paid by mobile salaries, and the remaining 169 employees in the control group continued to be paid by cash payments for the duration of the research study.[27] Baseline administrative and survey data summarized in

[24]In both cases, the variable's distribution was divided into above and below the median, and the stratification was implemented using that definition.

[25]Our results are robust to excluding employees from both of these provinces from the analysis.

[26]The Paktia and Paktika province offices were permanently closed in December 2012, necessitating endline surveys in November 2012. Ghazni province office was closed in January 2013, allowing for an endline survey in December 2012. All remaining provinces had their endline face-to-face survey conducted in February 2013, followed by one additional month of phone surveys prior to the end of the study. Due to the staggered rollout of the intervention and office closures, the number of monthly survey waves varies by provincial office location, from two phone survey waves in Ghazni, Paktia and Paktika to seven phone survey waves in Kabul; all offices had two in-person survey waves. We attempted a total of 2,049 individual surveys, or an average of 6 waves per employee. Of these, 1,711 (83.5%) were successfully conducted, resulting in a pooled survey non-response rate of 16.5% – or roughly 2.75% attrition per survey wave.

[27]As a reminder, all payments were implemented by CADG, significantly reducing the likelihood of non-compliance. The randomization pool included additional employees who had their employment terminated after assignment but before treatment was implemented, so they are excluded from this analysis. We also exclude from our analysis approximately one dozen CADG employees who had participated in the mobile

Appendix Table A8 indicates balance on employee observables such as age, marital status, number of children, ethnicity, tenure, salary, and usage of formal banks and hawala system.

5.2 Experimental Results

Administrative and survey data summarized in Table 2 shows monthly M-Paisa account usage, violence exposure and expectations, and other economic survey data. M-Paisa account usage data includes monthly average account balance, monthly total transaction counts, and self-reported travel time and costs to M-Paisa agents. Employees report high-levels of violence exposure with 21% of monthly survey responses affirmative to the question "Has the neighborhood in which you currently live experienced an attack in the previous calendar month?" We measure violence expectations using the following survey question, which was collected from individual respondents on a monthly basis: "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood. Is this extremely likely, very likely, somewhat likely, not very likely, or extremely unlikely?" When coded on a Likert scale, where 0 is extremely likely and 4 is extremely unlikely, this variable takes on an average value of 1.66 with a standard deviation of 1.13. For our analysis, we define a dummy variable Expects Violence_{it} that equals one if respondent i answered either "extremely likely" or "very likely" in month t.[28] Additional monthly survey data reported in this table includes monthly cash savings, expenditures, bank savings and cash transfers to friends and family members. We also aggregate our administrative transaction data to the monthly level.

We estimate treatment impacts using variants of the following specification:

$$\text{Y}_{it} = \beta_1 * \text{Treat x Post}_{it} + \beta_2 * \text{Treat}_i + \gamma_t + \eta_i + \epsilon_{it} \tag{3}$$

salaries pilot project prior to the research study.

[28]This violence expectations variable is strongly correlated with our violence exposure variables, particularly Attack Last Month (=1), even when including employee and month fixed effects. We interpret it as a violence forecast based on a combination of updated priors based on recent exposure, private information and other subjective beliefs.

where Y_{it} is the outcome of interest for individual i in month t, Treat_i is a dummy equaling one for individuals receiving mobile salary payments, Post_t is a dummy variable equaling one after treatment begins, γ_t is a month fixed effect, and η_i is an employee fixed effect.

Estimates in columns (1) - (3) of Panel A of Table 3 indicate that treatment increased mobile money balances. Estimates do not change much when adding either strata or individual fixed effects. Our preferred specification in column (3) indicates that treatment increased mobile money balances by 6,118 AFA or about 2,095% of the control mean. This substantial treatment effect estimate is consistent with the program providing first-time access to mobile money.

We next extend this regression framework to check whether treatment effects vary by participants' expectations of future violence in columns (4) - (6) of Table 3.[29] This analysis reveals that treatment effects are considerably larger in months when participants do not expect violence. We also note that estimates remain stable across all of the estimated specifications. Treatment still induces mobile money use for those expecting violence, but their balances are about 4,489 AFA below those who do not expect violence (column 6).[30]

In Panel B of Table 3, we check for substitution from mobile money into cash savings in the treatment group by estimating the same specification as in Panel A with self-reported cash savings as the dependent variable. In columns (1) - (3), we see that cash savings also increase as a result of treatment, though these estimates are imprecise. In columns (4)-(6), we also find positive, but very imprecise, estimates for the triple-interaction term. Thus, the evidence for direct substitution from mobile money into cash savings is not conclusive.[31] Separately, when focusing only on within-employee variation in column (6), we note that

[29] This analysis uses a fully-saturated triple difference version of Equation (3); i.e., we interact Treat x Post X Expects Violence, and control for all two-way interactions and uninteracted variables.

[30] As Table A9 shows, our results in column (4)-(6) are qualitatively similar when separating the violence expectations variable into each answer, though grouping them improves power. In Table A10, we restrict the sample of Panel A to match estimation sample in Panel B and observe qualitatively similar results. In Table A11, we find that our results from Panel A of Table 3 are robust to including time-varying confounds such as household shocks, salary problems, salary satisfaction and expectations of future government control.

[31] In Appendix Table A12, we do not find a robust relationship between mobile salary treatment, violence expectations and other economic measures such as bank savings, individual transfers and expenditures.

the uninteracted coefficient on violence expectations is positive, large in magnitude and statistically significant, suggesting that subjects increase cash savings in months where they expect violence. We explore this relationship further in the next section.

Figure 3a presents a graphical representation of average daily M-Paisa balances in the treatment and control groups. While mobile money balances are slowly rising in the control group over time, they are not statistically distinguishable from zero during the period of the experimental study. By contrast, consistent with estimates in Table 3, the M-Paisa balances in the treatment group are large, even after cash withdrawals immediately following each pay period. Figure 3b depicts M-Paisa balances when participants are divided according to baseline expectations of violence. In this figure, groups are fixed over the full period for each individual using the value of Expects Violence in the baseline survey wave. On average, individuals in our treatment sample with higher baseline expectations of violence appear to maintain lower mobile money balances over time.

5.2.1 Panel Data Estimates - Violence Expectations, Cash Savings, and Mobile Money Balances

The data obtained during this experiment enable further examination of how subjects adjust financial decisions when thinking violence is more likely. Study participants report violence expectations every month, and the extent autocorrelation across months is low ($\rho = 0.12$; s.e. $= 0.03$), consistent with a constantly shifting security situation in Afghanistan. This variation permits us to estimate regressions of the form:

$$Y_{it} = \phi_1 * \text{Expects Violence}_{it} + \gamma_t + \eta_i + \epsilon_{it} \tag{4}$$

where Y_{it} is either cash savings or mobile money balances for individual i in month t. Table 4 reports corresponding estimates for the complete sample in panel A, only for participants in the treatment group in the post period (who have mobile wallets and so face a meaningful choice) in Panel B, and for the control group in Panel C.

Looking at the complete sample in Panel A, we see that M-Paisa balances are smaller (columns 1 - 3) and cash savings are larger (columns 4 - 6). The estimate for ϕ_1 in column 3 is not significant, likely because very few participants in the control group use mobile money.

We report results for the treatment group in the post-treatment period in Panel B. This group is particularly helpful for evaluating the model in Section 3, in that this group faces a real trade-off between saving using mobile money and cash because treatment provides them with regular deposits into their mobile wallet. For this group, there is evidence of substitution away from mobile money and toward cash in periods when subjects expect violence, although estimates in columns 5 and 6 are not significant at conventional levels. We also note that the reduction in mobile money is of similar magnitude to the increase in cash.

Last, looking at the control group in panel C, there is no obvious relationship between mobile money and violence (columns 1 - 3), primarily because very few individuals in this group use mobile money. However, as with Panels A and B, the control group in Panel C exhibits a similar preference for cash in periods when participants expect violence (columns 4 - 6) as observed in Panels A and B.

In Appendix Table A13, we restrict the sample of columns (1)-(3) to match the estimation sample in columns (4)-(6) for which self-reported cash savings data is available and observe qualitatively similar results on M-Paisa balances.[32]

5.3 Discussion

Why do we observe individuals responding to violence by reallocating their financial portfolios to cash from mobile money? In examining this question, we consider the precautionary motive (Keynes, 1936). If current conflict portends a more unstable future, the experience of violence may cause individuals to update their beliefs. Correspondingly, the ability to

[32]In Table A14, high violence beliefs are characterized by faster withdrawals following pay day, consistent with an interpretation of substituting from mobile savings to cash savings when violence expectations rise.

respond flexibly to changing circumstances may feel more urgent, creating a preference for liquidity. To consume from mobile money, it must first be converted to cash from an agent.[33] By this logic, violence should increase the relative demand for cash.

On the other hand, mobile money offers potential security advantages over cash. There are at least three reasons that these may not be enough to compensate for the reduction in liquidity. First, the violence (and corresponding expectations) we measure relate to insurgency and thus political instability. We do not observe direct predation from theft or bribery or other forms of violence that are associated with a risk of carrying cash. Second, eruptions of violence in Afghanistan have historically driven outward migration, usually to Pakistan and Iran.[34] Mobile money users tend to be wealthier, especially in our CADG sample, and may be considering whether to leave Afghanistan, but mobile money is not convertible outside of Afghanistan. Third, the liquidity of mobile money might be a function of levels of violence. Mobile money operators based in insecure regions receive a premium from the mobile operator to transact mobile money and refuse to operate altogether in highly unstable regions. If employees are concerned about agent coverage during periods of violence, this could trigger a liquidity run that becomes self-fulfilling.[35]

6 Violence and Cash Savings: Survey Data

We test the relationship between violence expectations and cash savings in an independent, national sample from Afghanistan, as described by Callen et al. (2014). These data, collected in December 2010, reflect 468 different primary sampling units (election polling center

[33] An exception to this is a small number of locations in Kabul that directly accepted mobile money as payment during this period. In results available on request, we replicate our administrative data results from Table 1 restricting the analysis to Kabul. We still find a negative and significant relationship which is consistent with the fact that this is a small number of locations.

[34] According the United Nations High Commissioner for Refugees (UNHCR), from 2002-2013, 3.8 million Afghans, about 12.75 percent of Afghanistan's total population, have repatriated from Pakistan alone, with roughly 1.6 million Afghan refugees remaining there (United Nations High Commissioner on Refugees, 2014).

[35] In Blumenstock et al. (2015), we examine employee welfare outcomes from this experiment using self-reported data on salary satisfaction, economic behaviors, and corruption and security perceptions. While we document large cost savings for the employer, we find little consistent evidence that mobile salary payments had a significant impact on employee well-being.

catchments) across 19 provincial capitals.[36] Three features of these data provide a means of testing whether our results might generalize beyond our experimental sample. First, they afford much greater geographic coverage. Second, they reflect a period two years prior to the mobile salary experiment. Last, they contain nearly identical savings and violence expectations modules as the experimental data discussed in the preceding section.[37] A natural drawback of these data are that they comprise only one cross-section, limiting our ability to control for time-invariant confounds.

We use a subset of the Callen et al. (2014) data to investigate whether violence expectations per se, rather than several other factors – such as risk aversion, present bias, time discounting, and optimism – are related to the decision to hold cash. These data come from 12 less conservative provinces among the 19 covered in the survey, and they cover 287 polling center precincts. As discussed in detail in Callen et al. (2014), questions involving risk and games that resemble gambling are potentially sensitive for Muslims.[38] Of the 2,027 respondents contacted in these polling precincts, only 1,127 respondents consented to participate in the experimental component of the survey (of which, 1,122 responded to the question measuring violence forecasts and only 972 also responded to the Holt-Laury risk task). Estimates using the 19-province sample are reported in Table 5 and estimates using the 12-province sample are reported in Table 6.

[36] Enumerators were told to begin at the coordinates of the polling center and survey either 6 or 8 subjects. Surveys were conducted in individuals' homes. Enumerators adhered to the right-hand rule random selection method and respondents within houses were selected according to a Kish grid (Kish, 1949). Keeping with Afghan custom, men and women were interviewed by field staff of their own gender.

[37] Both modules used identical text for the expectations elicitation question: 'In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood.' The 2010 survey (from Callen et al. (2014)) used an 11-point Likert scale for responses, while the 2013 survey (from Section 5 above) used a 5-point scale. To facilitate comparison between these two scales, we define the independent variable Expects Violence (=1) as an indicator for responses above the median value in the corresponding sample (4 on the 11-point scale in this section, and 3 on the 5-point scale in Section 5). The results are qualitatively similar using alternative thresholds.

[38] The provinces covered in the survey are Badakhshan, Balkh, Bamyan, Daikondi, Faryab, Herat, Juzjan, Kabul, Kapisa, Panjshir, Parwan, and Samangan. In additions, before measuring risk and time preferences, we had our interviewers read a fixed informed consent script, asking individuals if they were willing to answer a few questions about uncertain outcomes. Of the 2,027 respondents contacted, 1,127 respondents consented to participate in the experimental component of the survey. The complete consent script is reported in the appendix to (Callen et al., 2014).

Table 5 presents estimates using this 2010 sample, where all columns include demographic controls and province fixed-effects. Column (1) reports the relationship between cash savings and an indicator variable for exposure to violence (defined as a violent attack recorded in the SIGACTs database in a 1km radius of the polling center within the past 3 years).[39] Column (2) reports the relationship between cash savings and an indicator variable for violence expectations, where the indicator equals one for an above median value on the ten-point Likert scale. Consistent with our earlier results, both violence exposure and violence expectations are associated with higher cash savings. Column (3) shows that the relationship between cash savings and individual expectations of violence is robust to controlling for violence exposure. Column (4) shows that the interaction term between exposure and expectations is negative but not significant at conventional levels while the direct effects of both variables remain significant, and column (5) demonstrates that results are qualitatively similar when not trimming the top .5% of outliers in cash savings from the sample.

Our violence expectations question asks subjects to directly state their subjective beliefs in the likelihood of a particular state of the world: "insurgent-related violence will occur in your neighborhood." A substantial literature discusses the elicitation of future probabilities and a large number of studies use Likert scale responses about a future event as a means of obtaining a proxy for subjective beliefs about future events. Delavande et al. (2011) provide a review of efforts to elicit subjective probabilities in developing countries, arguing that point estimates of the probability events may afford some advantages over using a Likert scale, but that Likert scale measures provide valid proxies. More relevant to our study, Delavande and Kohler (2009) show that individuals' Likert scale responses about the probability that they have HIV successfully predicts their actual status.

In practice, survey measures of violence forecasts could also reflect a number of confounds

[39] Unfortunately, this survey does not provide similar fine-grained individual location data as available from cell phone records in Section 4, though we exploit the same geocoded violence data. For consistency with Callen et al. (2014), our measure of violence exposure employs a narrower 1km radius around the coordinates of a common landmark, in this case the polling center. Reported results are robust to alternative radius specifications, as well as to the exclusion of demographic controls and province fixed effects.

including: (i) general optimism; (ii) risk aversion; (iii) discount factors; and (iv) present bias. Table 6 includes measures of each of these confounds as an additional regressor.[40] Reassuringly, the magnitude of the coefficient is stable and remains significant, providing additional evidence that the Likert scale measure of violence expectations contains additional information beyond that available in the set of potential confounds.

7 Conclusion

The main finding in this paper is that when people expect violence, they are less likely to adopt and use mobile money and more likely to hold cash. This conclusion is supported by three separate, but complementary, research designs: one based on a large administrative dataset of mobile money transactions; one using panel survey data from a randomized control trial; and one from a cross-sectional household survey.

We focus on mobile money because it has the potential to be a transformative financial technology in developing economies (cf. Suri, 2017). The vision is that it can leapfrog traditional brick-and-mortar banking institutions in the same way that mobile phones eliminated the need for poor countries to develop landline-based communications infrastructure. This, in turn, could speed up the process for providing unbanked populations access to a formal financial accounts.

Nonetheless, despite many years of focused effort both by international aid agencies and domestic telecommunications companies, mobile money has not yet seen widespread adoption in Afghanistan. The resounding message from our three empirical exercises is that people will want cash when they expect instability. Cash is the only financial technology that is guaranteed to provide a means of exchange during crises. It does not depend on a network of mobile money agents, who will not work when they fear for their safety, nor the

[40] Table 6 includes fewer observations than Table 5 for the reasons described above. Appendix Table A15 demonstrates that Table 5 is qualitatively similar when restricted to the sample of 1,122 respondents from columns 1-4 of Table 6, though the Attacks variable is no longer statistically significant at conventional levels. Appendix Table A16 demonstrates that columns (1) - (4) of Table 6 are also robust to restricting to the sample of 972 respondents used in columns (5) - (7) of Table 6.

corresponding regulatory, technological, or financial architecture that can seize up during local or national crises.

At the time of writing, Afghanistan is experiencing just such a crisis. When the Taliban entered Kabul on August 15th, citizens rushed to banks to empty their accounts; several weeks later, banks remain closed, and the money on deposit is of no practical use. These events resonate with our analysis of how violence and instability affect the functioning of financial systems. For people to rely on such systems, they must believe that they will continue to operate in the future. Violence, in contexts like Afghanistan, can undermine that belief.

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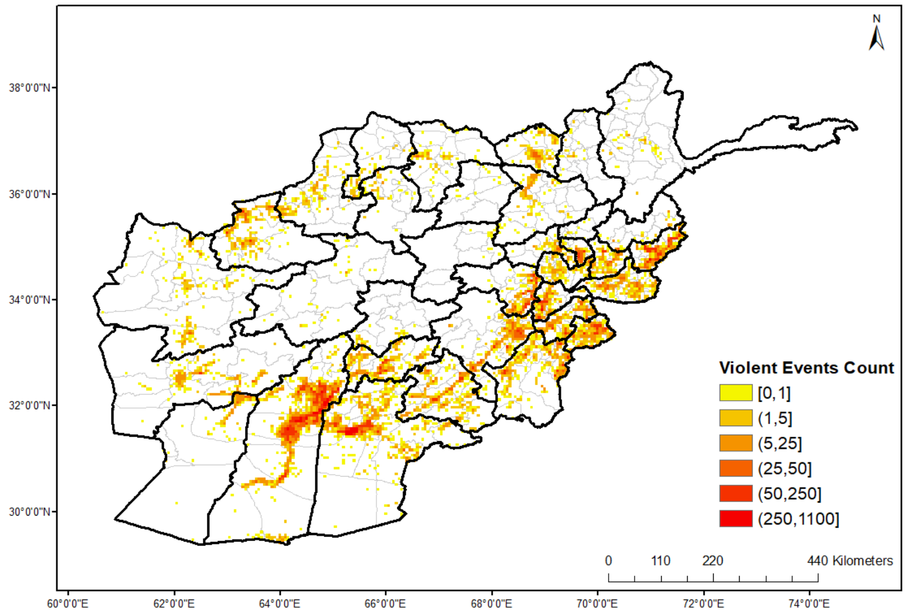
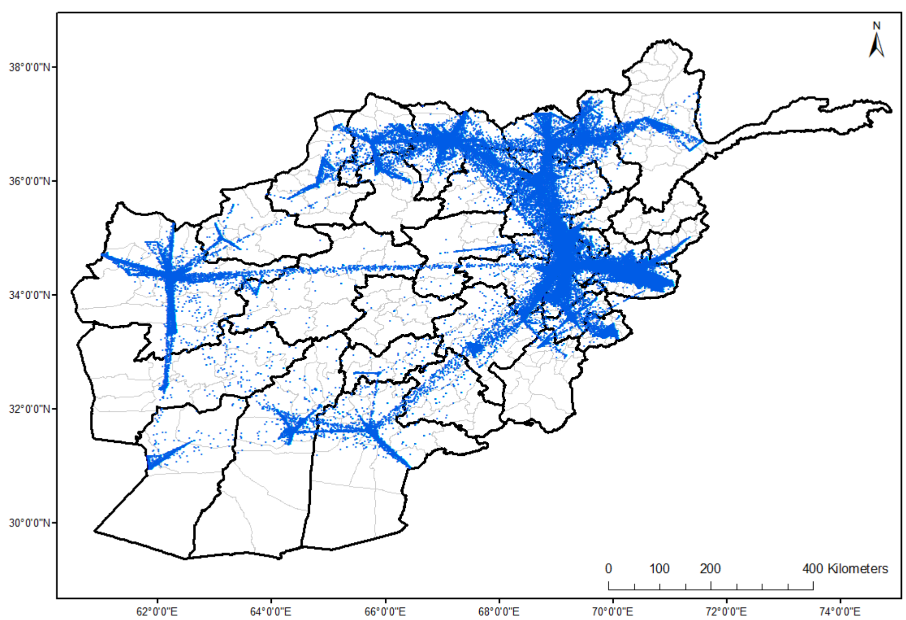
Tables and Figures

Figure 1: Administrative Dataset: Spatial Distribution of Violence & M-Paisa Users



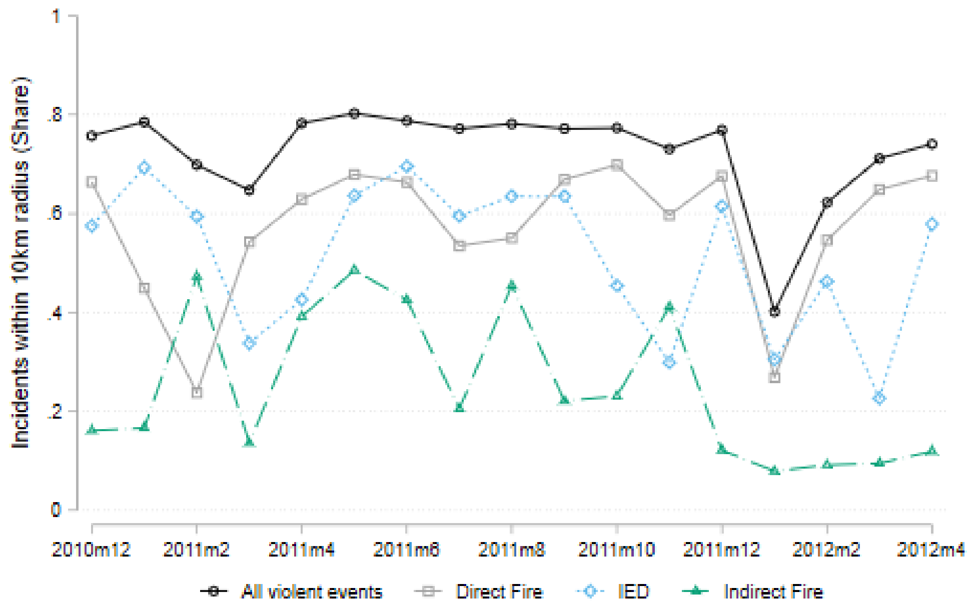
(a) Violent Incidents in Afghanistan (Dec 2010 - April 2012)



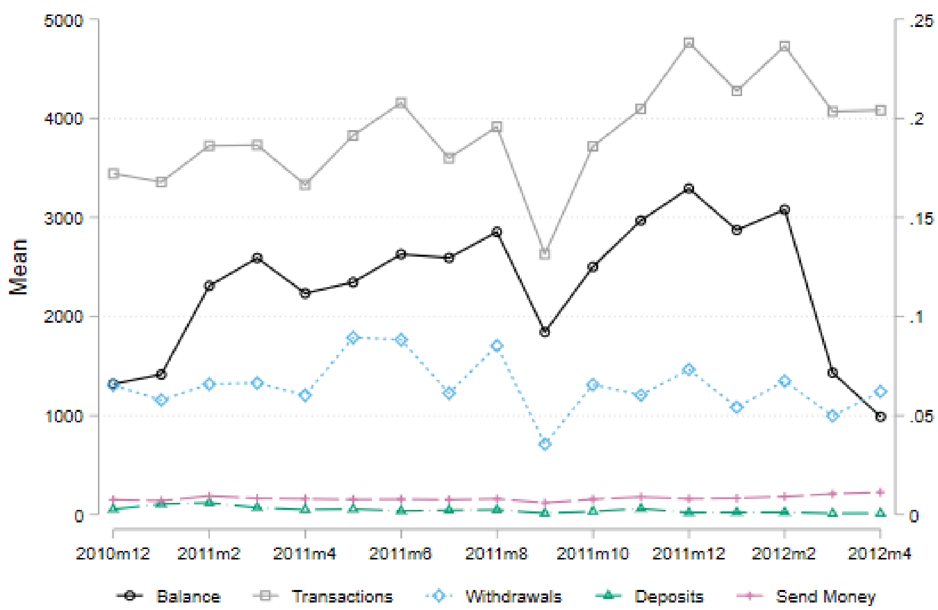
(b) Daily Center of Gravity (Dec 2010 - April 2012)

Notes: Top figure plots all violent incidents recorded by Afghan and International Security Assistance (ISAF) forces from December 2010-April 2012. Bottom figure plots the estimated daily Center of Gravity for each M-Paisa user in the sample over the period December 2010-April 2012. Refer to Section 4 for a description of the violence data and to Appendix A for a description of the Center of Gravity estimation methodology.

Figure 2: Administrative Dataset: Trends in Violence Exposure & M-Paisa Transactions



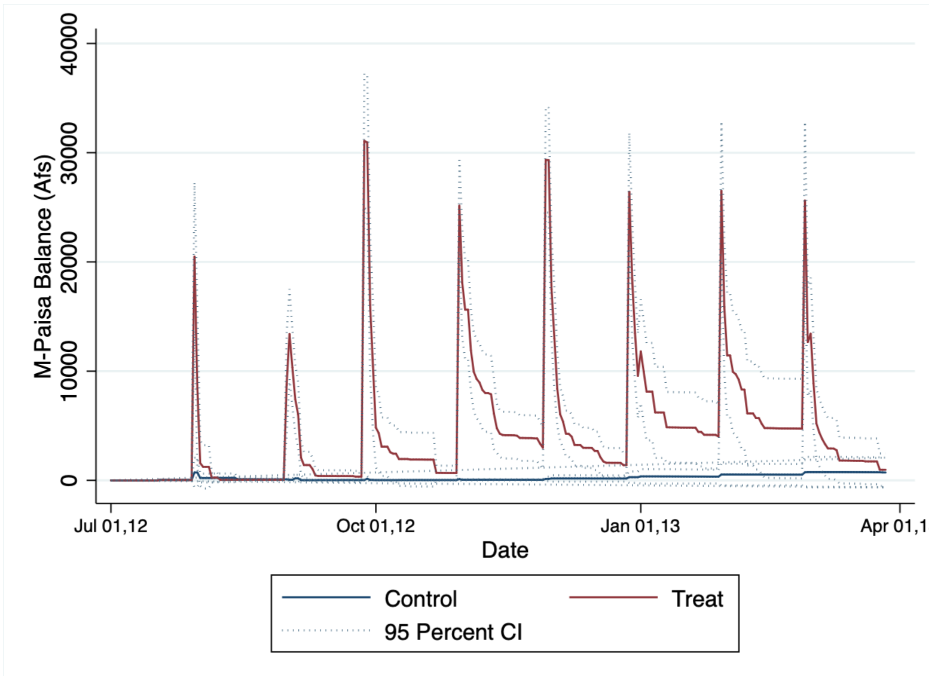
(a) Trends in Violence Exposure (Dec 2010 - April 2012)



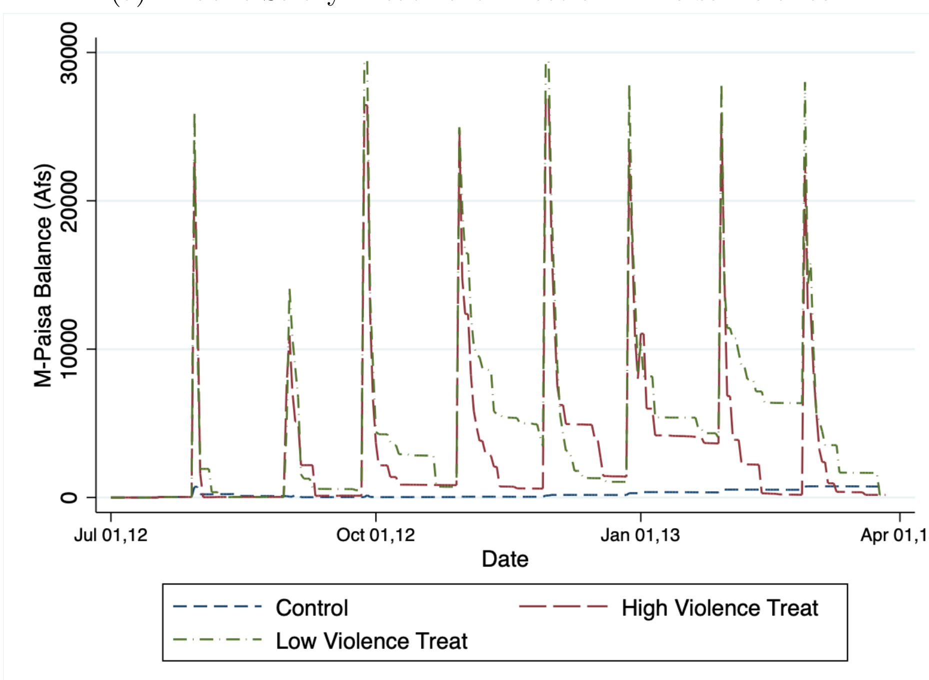
(b) Trends in M-Paisa Transactions (Dec 2010 - April 2012)

Notes: Panel (a) plots the share of M-Paisa account users experiencing at least one violent incident (direct fire, indirect fire, and IED incidents) within a 10-kilometer radius of their Center of Gravity location. Panel (b) plots average M-Paisa mobile money account balance in Afghanis (left axis) and average number of M-Paisa transactions, number of withdrawals, number of deposits, number of airtime purchases, and number of peer-to-peer mobile money transfers (right axis). Refer to Section 4 for a description of the violence and M-Paisa transaction data and variable definitions.

Figure 3: Experimental Dataset: Mobile Salary Treatment Effects & Violence Heterogeneity



(a) Mobile Salary Treatment Effect on M-Paisa Balance



(b) Mobile Salary Treatment Effect By Baseline Violence Expectations

Notes: Figures plot average daily M-Paisa balances in experimental sample described in Section 4. Top figure plots treatment and control groups, where the treatment group (red line) was randomly assigned to receive mobile salary payments and control group (blue line) did not. Bottom figure divides the treatment group by survey respondents coded as Expects Violence (=1) (i.e. reported insurgent-related violence was either "Very Likely" or "Extremely Likely" in the next month) in their baseline survey wave (dashed red line) and those with Expects Violence (=0) in their baseline survey wave (dot-dash green line).

Table 1: Administrative Dataset: Violence and M-Paisa Use

Dependent Var.	M-Paisa Balance	Transactions (#)	Withdrawals (#)	Deposits (#)	Send Money (#)
	(1)	(2)	(3)	(4)	(5)
Panel A: All violent events					
Violent Event in 10 km (=1)	-133.574	-0.048***	-0.017***	-0.003**	-0.001***
	(112.591)	(0.012)	(0.003)	(0.001)	(0.000)
R-Squared	0.691	0.501	0.230	0.228	0.438
Panel B: Violent event type					
Direct Fire in 10 km (=1)	-3.951	-0.033***	-0.012***	-0.002**	-0.001*
	(75.725)	(0.010)	(0.003)	(0.001)	(0.000)
Indirect Fire in 10 km (=1)	-355.851***	-0.024***	-0.010***	-0.001	-0.001***
	(80.213)	(0.006)	(0.002)	(0.001)	(0.000)
IED Explode in 10 km (=1)	-263.258***	-0.027***	-0.010***	-0.002***	-0.001***
	(67.819)	(0.003)	(0.002)	(0.000)	(0.000)
Sample	Salary Users	Salary Users	Salary Users	Salary Users	Salary Users
Mean Dep Var	2375.339	0.196	0.065	0.002	0.008
# Individuals	7551	7551	7551	7551	7551
# Clusters	239	239	239	239	239
# Observations	75055	75055	75055	75055	75055
R-Squared	0.692	0.503	0.234	0.229	0.438
Month-Year FE	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
District Trends	YES	YES	YES	YES	YES

Notes: Dependent variable is monthly average M-Paisa mobile money account balance in Afghanis in column (1), the monthly average number of M-Paisa transactions in column (2), the monthly average number of withdrawals in column (3), the monthly average number of deposits in column (4), and the monthly average number of peer-to-peer mobile money transfers in column (5). Observation is an individual-month. Violence variable is a dummy for whether a violent attack was recorded in the SIGACTs dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user in Panel A. Panel B splits violence variable by violent attack category. Refer to Section 3 for a description of each category. Robust standard errors, clustered at district level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Trimming top 1% and bottom 1% of outliers in M-Paisa balance.

Table 2: Experimental Dataset: Summary Statistics

Variable	Mean	Std. Dev.	N
M-Paisa Usage (admin data):			
M-Paisa Balance (Afs)	3153.96	12279.34	1418
Transactions (#)	1.62	2.36	1418
Deposits (#)	0	0.03	1418
Deposits (Afs)	0.35	13.28	1418
Withdrawals (#)	0.38	0.53	1418
Withdrawals (Afs)	11440.85	22415.48	1418
M-Paisa Agent Accessibility (survey data):			
Travel Time to M-Paisa Agent (minutes)	90.06	69.82	1407
Travel Cost to M-Paisa Agent (Afs)	74.62	137.61	1398
Violence and Expectations (survey data):			
Attack Last Month (=1)	0.21	0.40	1414
Expects Violence (=1)	0.24	0.43	1418
Savings and Expenditure (survey data):			
Cash Savings (Afs)	5014.36	18600.82	1341
Bank Savings (Afs)	6185.45	42859.18	1352
Transfers (Afs)	8143.14	18896.36	1418
Expenditure (Afs)	27185.80	50755.75	1418

Notes: Summary statistics for administrative and survey data from experimental sample as discussed in Section 5. Unit of observation is an employee-month. Sample includes 340 employees who are surveyed multiple times; see Section 5.1 for more details. Sample restricted to observations with Expects Violence (=1) variable non-missing and and trimming top .5% of cash outliers; some variables have fewer than 1418 observations due to survey non-response.

Table 3: Experimental Dataset: Violence Expectations, Mobile Money Balance and Cash Savings

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:			M-Paisa Balance (Afs)			
Mobile Salary Treatment x Post	6940.83***	6669.85***	6117.62***	7802.61***	7709.49***	7169.27***
	(1150.57)	(1057.61)	(954.02)	(1388.57)	(1374.56)	(1429.11)
Mobile Salary Treatment x Post x Expects Violence				-4077.51***	-4132.47**	-4488.86**
				(1418.53)	(1796.32)	(2226.22)
Expects Violence (=1)				29.36	-1251.90	470.46
				(58.80)	(840.56)	(395.99)
Control Mean Dep Var	278.60	278.60	278.60	278.60	278.60	278.60
# Employees	334	334	334	334	334	334
# Observations	1418	1418	1418	1418	1418	1418
R-Squared	0.09	0.18	0.44	0.10	0.19	0.44
Panel B:			Cash Savings (Afs)			
Mobile Salary Treatment x Post	4969.14	4705.15	3128.42	4005.73	3275.98	376.82
	(3032.75)	(2853.01)	(2412.01)	(2974.61)	(2750.17)	(1836.03)
Mobile Salary Treatment x Post x Expects Violence				3038.69	5056.46	7344.39
				(7825.89)	(7501.32)	(6857.71)
Expects Violence (=1)				4015.26	3867.65	8197.52**
				(5024.04)	(5095.17)	(4072.51)
Control Mean Dep Var	4618.86	4618.86	4618.86	4618.86	4618.86	4618.86
# Employees	333	333	333	333	333	333
# Observations	1341	1341	1341	1341	1341	1341
R-Squared	0.00	0.09	0.46	0.01	0.09	0.47
Month FE	YES	YES	YES	YES	YES	YES
Strata FE	NO	YES	-	NO	YES	-
Employee FE	NO	NO	YES	NO	NO	YES

Notes: Dependent variable is the M-Paisa mobile money account balance in Panel A and self-reported cash holdings in Panel B, and observation is an employee-month. Average exchange rate was approximately 50 Afghanis to the dollar during study period. Standard errors clustered at the employee level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The Expects Violence subgroups correspond to responses to the question "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood. Is this extremely likely, very likely, somewhat likely, not very likely, or extremely unlikely?" Extremely likely and very likely are coded as Expects Violence. All columns include covariates for Treat (=1) and Post (=1); columns 4, 5 and 6 also include covariates for Treat x Expects Violence and Post x Expects Violence. Regressions include month, strata and employee fixed effects as noted; strata fixed effects are absorbed by employee fixed effects in columns 3 and 6. Strata include provinces, share of income transfered to family (above/below median), and level of monthly expenditures on mobile airtime (above/below median). Trimming top .5% of outliers in cash savings.

Table 4: Experimental Dataset: Violence Expectations by Treatment Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample	M-Paisa Balance (Afs)			Cash Savings (Afs)		
Expects Violence (=1)	-1444.64**	-1631.00**	-580.59	3904.36**	3239.70**	3620.30**
	(567.43)	(686.40)	(494.13)	(1602.01)	(1594.53)	(1596.17)
Sample	All	All	All	All	All	All
Mean Dep Var	3153.96	3153.96	3153.96	5014.36	5014.36	5014.36
# Employees	334	334	334	333	333	333
# Observations	1418	1418	1418	1341	1341	1341
R-Squared	0.03	0.13	0.43	0.01	0.09	0.46
Panel B: Treat x Post Only	M-Paisa Balance (Afs)			Cash Savings (Afs)		
Expects Violence (=1)	-3597.08***	-3645.13**	-3303.49**	4768.43*	3689.09	2346.99
	(1342.43)	(1425.39)	(1400.61)	(2576.74)	(2782.62)	(2415.46)
Sample	Treat x Post	Treat x Post	Treat x Post	Treat x Post	Treat x Post	Treat x Post
Mean Dep Var	7335.34	7335.34	7335.34	5617.90	5617.90	5617.90
# Employees	162	162	162	162	162	162
# Observations	583	583	583	553	553	553
R-Squared	0.04	0.25	0.49	0.01	0.15	0.62
Panel C: Control Group Only	M-Paisa Balance (Afs)			Cash Savings (Afs)		
Expects Violence (=1)	184.25	348.11	331.43	3755.79	3197.99	4700.97*
	(188.35)	(317.41)	(326.63)	(2462.83)	(2520.90)	(2574.58)
Sample	Control	Control	Control	Control	Control	Control
Mean Dep Var	278.60	278.60	278.60	4618.86	4618.86	4618.86
# Employees	167	167	167	166	166	166
# Observations	693	693	693	646	646	646
R-Squared	0.00	0.12	0.31	0.00	0.04	0.41
Month FE	YES	YES	YES	YES	YES	YES
Strata FE	NO	YES	-	NO	YES	-
Employee FE	NO	NO	YES	NO	NO	YES

Notes: Dependent variable is the M-Paisa mobile money account balance in columns (1)-(3) and self-reported cash holdings in columns (4)-(6) and observation is an employee-month. Average exchange rate was approximately 50 Afghanis to the dollar during study period. Standard errors clustered at the employee level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The Expects Violence subgroups correspond to responses to the question "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood. Is this extremely likely, very likely, somewhat likely, not very likely, or extremely unlikely?" Extremely likely and very likely are coded as Expects Violence. Regressions include month, strata and employee fixed effects as noted; strata fixed effects are absorbed by employee fixed effects in columns 3 and 6. Strata include provinces, share of income transfered to family (above/below median), and level of monthly expenditures on mobile airtime (above/below median). Trimming top .5% of outliers in cash savings.

Table 5: Household Survey Dataset: Violence and Cash Savings

Dependent Variable:	Cash Savings (Afs)				
	(1)	(2)	(3)	(4)	(5)
Attacks (=1)	221.39**		222.24**	246.94**	408.84**
	(88.39)		(88.19)	(110.69)	(164.36)
Expects Violence (=1)		143.59*	145.20*	165.58*	196.19
		(86.39)	(86.82)	(100.00)	(119.33)
Attacks x Expects				-50.63	-100.48
				(157.46)	(214.59)
Constant	600.28***	623.27***	546.72***	538.91***	617.87***
	(137.88)	(138.24)	(140.10)	(139.87)	(172.48)
Sample	Trimmed	Trimmed	Trimmed	Trimmed	All
Mean Dep Var	903.33	903.33	903.33	903.33	990.42
# Clusters	468	468	468	468	468
# Observations	3033	3033	3033	3033	3047
R-Squared	0.148	0.146	0.149	0.149	0.114
Demographic Controls	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES

Notes: Dependent variable is self-reported cash holdings in Afghanis, and observation is an individual respondent in a 19 province survey during 2011 (see paper text for more details). Average exchange rate was approximately 50 Afghanis to the dollar during survey period. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The Attacks variable records whether a polling center had experienced an attack within 1km radius in the previous 3 years as recorded in the SIGACTs dataset (see paper text for more details). The Expects Violence subgroups correspond to responses to the question "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood." Respondents were given a 0-10 point likert scale where 10 represented a certainty of violence forecast; responses above the median (corresponding to a 5 or higher on the scale) are coded as Expects Violence. Demographic controls include age, gender, education, employment, and risk attitudes. Trimming top .5% of outliers in cash savings in columns (1) - (4).

Table 6: Household Survey Dataset: Violence and Cash Savings - Robustness

Dependent Variable:	Cash Savings (Afs)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Expects Violence (=1)	284.96*	293.47*	299.57*	305.33*	337.26*	320.90*	283.87
	(170.78)	(171.00)	(169.63)	(168.67)	(184.97)	(187.33)	(188.02)
Monthly Discount Factor	-2845.62					-4135.38	-4082.08
	(2220.88)					(3002.02)	(3048.89)
Present-Bias Paramenter		-2463.36				637.57	761.05
		(2568.11)				(3626.19)	(3584.23)
Ladder of Life (0-10)			30.23			10.77	14.30
			(40.52)			(42.25)	(41.15)
Financial Risk Likert (0-10)				47.82		52.87	11.75
				(40.29)		(45.80)	(44.98)
Holt-Laury Risk Measure					736.22*	692.21*	90.37
					(393.09)	(377.71)	(421.16)
Constant	3424.06	3148.31	620.96***	660.31***	371.38*	3477.68	3407.36
	(2093.28)	(2503.47)	(188.63)	(102.10)	(223.41)	(2752.22)	(2748.00)
# Clusters	287	287	287	287	286	286	286
# Observations	1122	1122	1122	1122	972	972	972
R-Squared	0.351	0.350	0.349	0.351	0.378	0.385	0.406
Demographic Controls	NO	NO	NO	NO	NO	NO	YES
Polling Center FE	YES	YES	YES	YES	YES	YES	YES

Notes: Dependent variable is self-reported cash holdings in Afghanis, and observation is an individual respondent in a 19 province survey during 2011 (see paper text for more details). Average exchange rate was approximately 50 Afghanis to the dollar during survey period. Robust standard errors clustered at the polling center level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The Expects Violence subgroups correspond to responses to the question "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood." Respondents were given a 0-10 point likert scale where 10 represented a certainty of violence forecast; responses above the median (corresponding to a 5 or higher on the scale) are coded as Expects Violence. Demographic controls include age, gender, education, employment, and risk attitudes. Trimming top .5% of outliers in all columns.

On-line Appendix: Not for Publication

A1 Appendix Tables and Figures

Table A0: R^2 from Predicting Residual Violence

	Linear Model			Regression Trees with 10-Fold CV		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Lags in violence						
R^2	0.009	0.007	0.010	0.011	0.009	0.013
# Observations	67506	59957	52999			
# Lags in violence	1	2	3	1	2	3
# Lags in M-Paisa	-	-	-	-	-	-
Panel B: Lags in violence and M-Paisa Balance						
R^2	0.009	0.007	0.010	0.008	0.008	0.018
# Observations	67506	59957	52999			
# Lags in violence	1	2	3	1	2	3
# Lags in M-Paisa	1	2	3	1	2	3
Panel C: Trends in violence (e.g. $\Delta v_{t-1} = v_{t-1} - v_{t-2}$)						
R^2	0.003	0.003	0.004	0.006	0.010	0.022
# Observations	59957	52999	46576			
# Trends viol.	1	2	3	1	2	3
# Trends M-Paisa	-	-	-	-	-	-
Panel D: Trends in violence and M-Paisa Balance						
R^2	0.003	0.003	0.005	0.007	0.011	0.035
# Observations	59957	52999	46576			
# Trends viol.	1	2	3	1	2	3
# Trends M-Paisa	-	-	-	-	-	-

Notes: Each cell gives the R^2 from regressions using as outcome the estimated residual from the following model $Violence_{it} = \pi_i + \mu_t + \eta_d t + \xi_{it}$ where each term is defined as in Equation (1) in the text. "Linear model" in columns (1)-(3) refers to regressions using the specified lags in violence (Panel A), lags in violence and M-Paisa balances (Panel B), trends in violence (Panel C), and trends in violence and M-Paisa balances (Panel D) as predictors of these residuals. Trends in violence refers to using differences in violence as predictors, for example, $\Delta v_{t-1} = v_{t-1} - v_{t-2}$, $\Delta v_{t-2} = v_{t-2} - v_{t-3}$, etc. Columns (4)-(6) uses regression trees with 10-fold cross validation to predict the residuals using the specified number of lags/trends in violence and M-Paisa balances. Columns (5)-(8) present the R^2 for the cross-validation sample.

Table A1: Administrative Dataset: Violence and M-Paisa Use, All Users

Dependent Var.	M-Paisa Balance	Transactions (#)	Withdrawals (#)	Deposits (#)	Send Money (#)
	(1)	(2)	(3)	(4)	(5)
Panel A: All violent events					
Violent Event in 10 km (=1)	-45.878	-0.080***	-0.012***	-0.012***	-0.001***
	(83.108)	(0.013)	(0.002)	(0.002)	(0.000)
R-Squared	0.704	0.466	0.369	0.337	0.381
Panel B: Violent event type					
Direct Fire in 10 km (=1)	32.166	-0.046***	-0.009***	-0.005***	-0.000*
	(42.775)	(0.008)	(0.002)	(0.001)	(0.000)
Indirect Fire in 10 km (=1)	-252.236***	-0.024***	-0.008***	-0.002*	-0.000**
	(61.233)	(0.005)	(0.002)	(0.001)	(0.000)
IED Explode in 10 km (=1)	-127.264**	-0.046***	-0.007***	-0.008***	-0.001***
	(53.811)	(0.004)	(0.002)	(0.002)	(0.000)
Sample	All Users	All Users	All Users	All Users	All Users
Mean Dep Var	1734.143	0.189	0.044	0.011	0.006
# Individuals	12722	12722	12722	12722	12722
# Clusters	259	259	259	259	259
# Observations	114171	114171	114171	114171	114171
R-Squared	0.704	0.466	0.372	0.337	0.381
Month-Year FE	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
District Trends	YES	YES	YES	YES	YES

Notes: Dependent variable is monthly average M-Paisa mobile money account balance in Afghanis in column (1), the monthly average number of M-Paisa transactions in column (2), the monthly average number of withdrawals in column (3), the monthly average number of deposits in column (4), and the monthly average number of peer-to-peer mobile money transfers in column (5). Observation is an individual-month. Violence variable is a dummy for whether a violent attack was recorded in the SIGACTs dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user in Panel A. Panel B splits violence variable by violent attack category. Refer to Section 3 for a description of each category. Robust standard errors, clustered at district level, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Trimming top 1% and bottom 1% of outliers in M-Paisa balance.

Table A2: Administrative Dataset: Violence and M-Paisa Use, using Different Radii

Dependent Var.	M-Paisa Balance	Transactions (#)	Withdrawals (#)	Deposits (#)	Send Money (#)
	(1)	(2)	(3)	(4)	(5)
Panel A: All violent events					
Violent Event in 5 km (=1)	-130.370	-0.053***	-0.019***	-0.003**	-0.001***
	(133.331)	(0.014)	(0.003)	(0.001)	(0.000)
Violent Event in (5,10] km (=1)	-138.357	-0.039***	-0.014***	-0.002*	-0.001*
	(94.157)	(0.010)	(0.002)	(0.001)	(0.001)
R-Squared	0.691	0.501	0.231	0.228	0.438
Panel B: Violent event type					
Direct Fire in 5 km (=1)	68.531	-0.035***	-0.013***	-0.002**	-0.000
	(97.000)	(0.011)	(0.003)	(0.001)	(0.000)
Direct Fire in (5,10] km (=1)	-80.932	-0.032***	-0.012***	-0.002**	-0.001**
	(84.158)	(0.009)	(0.003)	(0.001)	(0.000)
Indirect Fire in 5 km (=1)	-387.982***	-0.028***	-0.012***	-0.001	-0.001***
	(104.391)	(0.007)	(0.002)	(0.001)	(0.000)
Indirect Fire in (5,10] km (=1)	-338.785***	-0.021***	-0.008***	-0.001	-0.000
	(83.943)	(0.005)	(0.002)	(0.001)	(0.000)
IED Explode in 5 km (=1)	-214.712**	-0.028***	-0.010***	-0.002***	-0.001***
	(87.284)	(0.004)	(0.002)	(0.000)	(0.000)
IED Explode in (5,10] km (=1)	-317.234***	-0.024***	-0.008***	-0.001***	-0.001
	(99.471)	(0.003)	(0.002)	(0.000)	(0.000)
Sample	Salary Users	Salary Users	Salary Users	Salary Users	Salary Users
Mean Dep Var	2375.339	0.196	0.065	0.002	0.008
# Individuals	7551	7551	7551	7551	7551
# Clusters	239	239	239	239	239
# Observations	75055	75055	75055	75055	75055
R-Squared	0.692	0.503	0.235	0.229	0.438
Month-Year FE	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
District Trends	YES	YES	YES	YES	YES

Notes: Dependent variable is monthly average M-Paisa mobile money account balance in Afghanis in column (1), the monthly average number of M-Paisa transactions in column (2), the monthly average number of withdrawals in column (3), the monthly average number of deposits in column (4), and the monthly average number of peer-to-peer mobile money transfers in column (5). Observation is an individual-month. In Panel A, "Violent Event in 5km" is a dummy for whether a violent attack was recorded in the SIGACTs dataset in a 5km radius of the Center of Gravity location of the M-Paisa account user. "Violent Event in (5,10] km" is a dummy for whether a violent attack was recorded in the SIGACTs dataset beyond 5km but within a 10km radius of the Center of Gravity location of the M-Paisa account user. Panel B splits the violence variables in Panel A by violent attack category. Refer to Section 3 for a description of each category. Robust standard errors, clustered at district level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Trimming top 1% and bottom 1% of outliers in M-Paisa balance.

Table A3: Administrative Dataset: Violence and M-Paisa Use, COG-nearest village match

Dependent Var.	M-Paisa Balance	Transactions (#)	Withdrawals (#)	Deposits (#)	Send Money (#)
	(1)	(2)	(3)	(4)	(5)
Panel A: All violent events					
Violent Event in 10 km (=1)	-84.344	-0.047***	-0.016***	-0.003**	-0.001***
	(139.557)	(0.010)	(0.002)	(0.001)	(0.000)
R-Squared	0.691	0.501	0.229	0.228	0.438
Panel B: Violent event type					
Direct Fire in 10 km (=1)	67.034	-0.034***	-0.012***	-0.002**	-0.000
	(75.159)	(0.008)	(0.002)	(0.001)	(0.000)
Indirect Fire in 10 km (=1)	-314.881***	-0.022***	-0.009***	-0.001*	-0.001***
	(84.750)	(0.005)	(0.002)	(0.001)	(0.000)
IED Explode in 10 km (=1)	-202.146***	-0.024***	-0.008***	-0.002***	-0.001**
	(68.818)	(0.003)	(0.002)	(0.000)	(0.000)
Sample	Salary Users	Salary Users	Salary Users	Salary Users	Salary Users
Mean Dep Var	2375.339	0.196	0.065	0.002	0.008
# Individuals	7551	7551	7551	7551	7551
# Clusters	239	239	239	239	239
# Observations	75055	75055	75055	75055	75055
R-Squared	0.692	0.502	0.232	0.229	0.438
Month-Year FE	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
District Trends	YES	YES	YES	YES	YES

Notes: Dependent variable is monthly average M-Paisa mobile money account balance in Afghanis in column (1), the monthly average number of M-Paisa transactions in column (2), the monthly average number of withdrawals in column (3), the monthly average number of deposits in column (4), and the monthly average number of peer-to-peer mobile money transfers in column (5). Observation is an individual-month. Violence variable is a dummy for whether a violent attack was recorded in the SIGACTs dataset in a 10km radius of the village closest to the Center of Gravity location of the M-Paisa account user in Panel A. Panel B splits violence variable by violent attack category. Refer to Section 3 for a description of each category. Robust standard errors, clustered at district level, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Trimming top 1% and bottom 1% of outliers in M-Paisa balance.

Table A4: Administrative Dataset: Violence and M-Paisa Use, Conditioning on Prior Exposure to Violence

Dependent Var.	M-Paisa Balance	Transactions (#)	Withdrawals (#)	Deposits (#)	Send Money (#)
	(1)	(2)	(3)	(4)	(5)
Violent Event in 10 km (=1)	-113.074	-0.027**	-0.010**	-0.000	-0.001***
	(76.256)	(0.012)	(0.004)	(0.000)	(0.000)
Total Violent Events up to $t-1$	1.007	0.000	-0.000*	0.000***	0.000***
	(1.356)	(0.000)	(0.000)	(0.000)	(0.000)
Sample	Salary Users	Salary Users	Salary Users	Salary Users	Salary Users
Mean Dep Var	2248.432	0.184	0.061	0.001	0.009
# Individuals	6958	6958	6958	6958	6958
# Clusters	232	232	232	232	232
# Observations	66907	66907	66907	66907	66907
R-Squared	0.702	0.600	0.319	0.425	0.456
Month-Year FE	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
District Trends	YES	YES	YES	YES	YES

Notes: Dependent variable is monthly average M-Paisa mobile money account balance in Afghanis in column (1), the monthly average number of M-Paisa transactions in column (2), the monthly average number of withdrawals in column (3), the monthly average number of deposits in column (4), and the monthly average number of peer-to-peer mobile money transfers in column (5). Observation is an individual-month. Violence variable is a dummy for whether a violent attack was recorded in the SIGACTs dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user. Total Violent Events up to $t-1$ refers to the total number of violent events recorded within a 10km radius of an individual's Center of Gravity location up to $t-1$. Robust standard errors, clustered at district level, in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Trimming top 1% and bottom 1% of outliers in M-Paisa balance.

Table A5: Administrative Dataset: Violence and M-Paisa Use, Fixed Effects Sensitivity

Dependent Var.	M-Paisa Balance				Transactions (#)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All violent events								
Violent Event in 10 km (=1)	-557.264	-499.064	-280.684***	-133.574	0.011	0.017*	-0.034***	-0.048***
	(371.302)	(371.922)	(99.970)	(112.591)	(0.007)	(0.009)	(0.010)	(0.012)
R-Squared	0.001	0.005	0.054	0.691	0.000	0.011	0.080	0.501
Panel B: By violent event type								
Direct Fire in 10 km (=1)	-224.970	-101.925	-117.520	-3.951	0.012**	0.013**	-0.026***	-0.033***
	(333.193)	(388.558)	(117.812)	(75.725)	(0.005)	(0.006)	(0.007)	(0.010)
Indirect Fire in 10 km (=1)	-339.861	-543.411*	-388.060***	-355.851***	-0.019**	-0.016*	-0.011*	-0.024***
	(282.985)	(293.321)	(127.761)	(80.213)	(0.008)	(0.009)	(0.007)	(0.006)
IED Explode in 10 km (=1)	-254.778	-277.401	-252.561***	-263.258***	0.007	0.010	-0.015***	-0.027***
	(261.252)	(260.837)	(77.611)	(67.819)	(0.006)	(0.007)	(0.005)	(0.003)
Sample	Salary	Salary	Salary	Salary	Salary	Salary	Salary	Salary
Mean Dep Var	2375.339	2375.339	2375.339	2375.339	0.196	0.196	0.196	0.196
# Individuals	7551	7551	7551	7551	7551	7551	7551	7551
# Clusters	239	239	239	239	239	239	239	239
# Observations	75055	75055	75055	75055	75055	75055	75055	75055
R-Squared	0.001	0.006	0.054	0.692	0.001	0.012	0.081	0.503
Month-Year FE	NO	YES	YES	YES	NO	YES	YES	YES
Individual FE	NO	NO	NO	YES	NO	NO	NO	YES
District Trends	NO	NO	YES	YES	NO	NO	YES	YES

Notes: Dependent variable is the average M-Paisa mobile money account balance in Afghanis in columns (1)-(4), and the average number of M-Paisa transactions in columns (5)-(8). Observation is an individual-month. Violence variable is a dummy for whether a violent attack was recorded in the SIGACTs dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user in Panel A. Panel B splits violence variable by violent attack category. Refer to Section 3 for a description of each category. Robust standard errors, clustered at district level, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Trimming top 1% and bottom 1% of outliers in M-Paisa balance.

Table A6: Administrative Dataset: Violence and M-Paisa Use, Adding District-level Controls

	M-Paisa Balance	Transactions (#)	Withdrawals (#)	Deposits (#)	Send Money (#)
	(1)	(2)	(3)	(4)	(5)
Panel A: All violent events, No District-level controls					
Violent Event in 10 km (=1)	-249.099	-0.058***	-0.017***	-0.005***	-0.002**
	(175.753)	(0.019)	(0.003)	(0.002)	(0.001)
R-Squared	0.688	0.611	0.420	0.331	0.468
Panel B: Violent event type, No District-level controls					
Direct Fire in 10 km (=1)	10.578	-0.047**	-0.016***	-0.004**	-0.001**
	(133.971)	(0.019)	(0.005)	(0.001)	(0.001)
Indirect Fire in 10 km (=1)	-466.162**	-0.028***	-0.006	-0.002	-0.002**
	(197.450)	(0.007)	(0.006)	(0.002)	(0.001)
IED Explode in 10 km (=1)	-861.580***	-0.015*	-0.009**	-0.001	0.000
	(180.010)	(0.008)	(0.004)	(0.001)	(0.001)
R-Squared	0.689	0.612	0.424	0.331	0.468
Panel C: All violent events, District-level controls					
Violent Event in 10 km (=1)	-188.330	-0.059***	-0.017***	-0.005***	-0.002**
	(172.163)	(0.019)	(0.004)	(0.002)	(0.001)
R-Squared	0.689	0.612	0.425	0.332	0.468
Panel D: Violent event type, District-level controls					
Direct Fire in 10 km (=1)	43.190	-0.049***	-0.016***	-0.004***	-0.001**
	(133.782)	(0.019)	(0.005)	(0.001)	(0.001)
Indirect Fire in 10 km (=1)	-524.728**	-0.027***	-0.004	-0.002	-0.002**
	(232.645)	(0.006)	(0.006)	(0.002)	(0.001)
IED Explode in 10 km (=1)	-812.330***	-0.016**	-0.009***	-0.001	0.000
	(173.839)	(0.007)	(0.003)	(0.001)	(0.001)
Sample	Salary Users	Salary Users	Salary Users	Salary Users	Salary Users
Mean Dep Var	2469.056	0.213	0.060	0.002	0.010
# Individuals	6298	6298	6298	6298	6298
# Clusters	188	188	188	188	188
# Observations	26906	26906	26906	26906	26906
R-Squared	0.689	0.613	0.429	0.332	0.468
Month-Year FE	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
District Trends	YES	YES	YES	YES	YES

Notes: Dependent variable is monthly average M-Paisa mobile money account balance in Afghanis in column (1), the monthly average number of M-Paisa transactions in column (2), the monthly average number of withdrawals in column (3), the monthly average number of deposits in column (4), and the monthly average number of peer-to-peer mobile money transfers in column (5). Observation is an individual-month. Violence variable is a dummy for whether a violent attack was recorded in the SIGACTs dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user. Includes district level-by-month controls for average age; share of females; share rural; share of population with primary, and secondary education; share of population receiving income from farming; average number of hours per day with electricity; share of the population that is Pashtun. District level controls obtained from repeated cross-sections of respondents from the Afghanistan Nationwide Quarterly Assessment Research (ANQAR) survey (Plumb et al., 2017). ANQAR data available for March, June, September, November, December 2011 and February, March 2012. Difference in estimates and number of observations between Panels A, B and Table 1 due to restricting original data to districts and months available in ANQAR data: 7 months (17 months in original sample) and 188 districts (239 in original sample).

Table A7: Administrative Dataset: Violence and M-Paisa Use, Non-Imputed Locations

Dependent Var.	M-Paisa Balance	Transactions (#)	Withdrawals (#)	Deposits (#)	Send Money (#)
	(1)	(2)	(3)	(4)	(5)
Panel A: All violent events					
Violent Event in 10 km (=1)	-51.974	-0.135***	-0.051***	-0.006**	-0.010**
	(107.945)	(0.017)	(0.005)	(0.003)	(0.004)
R-Squared	0.686	0.550	0.494	0.177	0.583
Panel B: Violent event type					
Direct Fire in 10 km (=1)	94.595	-0.089***	-0.035***	-0.003***	-0.009**
	(110.265)	(0.013)	(0.003)	(0.001)	(0.004)
Indirect Fire in 10 km (=1)	-785.571***	-0.065***	-0.027***	-0.002	-0.004**
	(134.041)	(0.006)	(0.006)	(0.002)	(0.002)
IED Explode in 10 km (=1)	-198.825*	-0.080***	-0.031***	-0.005**	-0.006**
	(103.571)	(0.008)	(0.005)	(0.002)	(0.003)
Sample	Salary Users	Salary Users	Salary Users	Salary Users	Salary Users
Mean Dep Var	2356.280	0.403	0.140	0.004	0.024
# Individuals	7304	7304	7304	7304	7304
# Clusters	231	231	231	231	231
# Observations	58696	58696	58696	58696	58696
R-Squared	0.686	0.552	0.496	0.177	0.583
Month-Year FE	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES
District Trends	YES	YES	YES	YES	YES

Notes: Dependent variable is monthly average M-Paisa mobile money account balance in Afghanis in column (1), the monthly average number of M-Paisa transactions in column (2), the monthly average number of withdrawals in column (3), the monthly average number of deposits in column (4), and the monthly average number of peer-to-peer mobile money transfers in column (5). Observation is an individual-month. Violence variable is a dummy for whether a violent attack was recorded in the SIGACTs dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user. Individual-month observations where individual did not make a call (and hence when location was imputed using last observed location) dropped from analysis. Robust standard errors, clustered at district level, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Trimming top 1% and bottom 1% of outliers in M-Paisa balance.

Table A8: Experimental Dataset: Balance Tests (Treatment = Mobile Salary)

	Cash	Mobile	Difference	p-value
Age	35.130	36.205	1.075	0.409
	[12.469]	[11.474]	(1.299)	.
Married (=1)	0.792	0.848	0.056	0.178
	[0.407]	[0.360]	(0.042)	.
Number Children	2.822	3.386	0.563	0.108
	[3.058]	[3.386]	(0.350)	.
Pashtun (=1)	0.762	0.788	0.026	0.578
	[0.427]	[0.410]	(0.046)	.
Tenure (Months)	12.345	11.582	-0.763	0.475
	[9.931]	[9.664]	(1.066)	.
Monthly Salary (1000 Afs)	34.037	35.555	1.518	0.666
	[26.925]	[37.018]	(3.514)	.
Monthly Airtime Bill (Afs)	724.398	736.404	12.007	0.725
	[312.042]	[309.930]	(34.084)	.
Family Transfer Share (=1)	0.508	0.511	0.003	0.936
	[0.326]	[0.323]	(0.036)	.
Formally Banked (=1)	0.283	0.268	-0.015	0.756
	[0.452]	[0.444]	(0.049)	.
Hawala User (=1)	0.219	0.216	-0.003	0.955
	[0.415]	[0.413]	(0.045)	.
Roshan User (=1)	0.515	0.497	-0.018	0.745
	[0.501]	[0.501]	(0.054)	.
Wants M-Paisa (=1)	0.310	0.312	0.002	0.965
	[0.464]	[0.465]	(0.050)	.
Observations	169	171		

Standard deviations in brackets and standard errors in parentheses.

Table A9: Experimental Dataset: Treatment Effects by Violence Expectations

	(1)	(2)	(3)
	M-Paisa Balance (Afs)		
Mobile Salary Treatment x Post	8221.40***	8641.70***	9047.30***
	(2072.37)	(2268.42)	(3062.82)
Mobile Salary Treatment x Post x Extremely Unlikely	1944.98	770.92	-362.31
	(3352.61)	(3378.89)	(4439.53)
Mobile Salary Treatment x Post x Not Very Likely	-2785.03	-3616.39	-7961.54**
	(2099.56)	(2676.47)	(3257.88)
Mobile Salary Treatment x Post x Very Likely	-3797.13*	-4092.17	-5356.30
	(2142.44)	(2550.08)	(3661.28)
Mobile Salary Treatment x Post x Extremely Likely	-7252.35***	-12371.65**	-11565.98**
	(2682.41)	(5360.41)	(5422.04)
Violence Extremely Unlikely	-65.92	-181.92	243.12
	(81.81)	(809.30)	(349.16)
Violence Not Very Likely	-39.74	-313.90	-1518.20
	(80.85)	(1081.98)	(1538.72)
Violence Very Likely	-4.76	-1360.30	194.79
	(70.12)	(909.58)	(288.01)
Violence Extremely Likely	-260.53	-5691.11	-506.58
	(300.07)	(4567.01)	(739.97)
Sample	All	All	All
Mean Dep Var	3153.96	3153.96	3153.96
# Employees	334	334	334
# Observations	1418	1418	1418
R-Squared	0.11	0.22	0.11
Month FE	YES	YES	YES
Strata FE	NO	YES	-
Employee FE	NO	NO	YES

Dependent variable is the M-Paisa mobile money account balance in Afghanis, and observation is an employee-month. Average exchange rate was approximately 50 Afghanis to the dollar during study period. Standard errors clustered at the employee level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The Expects Violence subgroups correspond to responses to the question "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood. Is this extremely likely, very likely, somewhat likely, not very likely, or extremely unlikely?" Strata include provinces, share of income transfered to family (above/below median), and level of monthly expenditures on mobile airtime (above/below median). Trimming top .5% of outliers in cash savings.

Table A10: Experimental Dataset: Violence Expectations, Mobile Money Balance and Cash Savings

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	M-Paisa Balance (Afs)					
Mobile Salary Treatment x Post	7092.73***	6894.47***	6185.75***	8086.27***	8001.21***	7280.21***
	(1205.02)	(1117.45)	(975.01)	(1455.78)	(1440.04)	(1451.45)
Mobile Salary Treatment x Post x Expects Violence				-4762.79***	-4401.40**	-4889.24**
				(1511.95)	(1868.59)	(2252.75)
Expects Violence (=1)				26.83	-1311.59	608.30
				(60.57)	(856.00)	(399.67)
Control Mean Dep Var	296.96	296.96	296.96	296.96	296.96	296.96
# Employees	333	333	333	333	333	333
# Observations	1341	1341	1341	1341	1341	1341
R-Squared	0.10	0.18	0.43	0.10	0.19	0.43
Panel B:	Cash Savings (Afs)					
Mobile Salary Treatment x Post	4969.14	4705.15	3128.42	4005.73	3275.98	376.82
	(3032.75)	(2853.01)	(2412.01)	(2974.61)	(2750.17)	(1836.03)
Mobile Salary Treatment x Post x Expects Violence				3038.69	5056.46	7344.39
				(7825.89)	(7501.32)	(6857.71)
Expects Violence (=1)				4015.26	3867.65	8197.52**
				(5024.04)	(5095.17)	(4072.51)
Control Mean Dep Var	4618.86	4618.86	4618.86	4618.86	4618.86	4618.86
# Employees	333	333	333	333	333	333
# Observations	1341	1341	1341	1341	1341	1341
R-Squared	0.00	0.09	0.46	0.01	0.09	0.47
Month FE	YES	YES	YES	YES	YES	YES
Strata FE	NO	YES	-	NO	YES	-
Employee FE	NO	NO	YES	NO	NO	YES

Notes: See Table 3 notes; sample in Panel A is restricted here to match the estimation sample from Panel B.

Table A11: Experimental Dataset: Treatment Effects by Violence Expectations - Robustness

Dependent Var.	M-Paisa Balance (Afs)			
	(1)	(2)	(3)	(4)
Mobile Salary Treatment x Post	6583.31***	5767.57***	6977.71***	7735.32***
	(1344.84)	(1027.98)	(1535.72)	(1748.58)
Mobile Salary Treatment x Post x Expects Violence	-4587.16**	-5328.01**	-4615.50**	-5131.05**
	(2264.56)	(2413.49)	(2274.12)	(2440.31)
Mobile Salary Treatment x Post x HH Shock	3567.14			
	(4852.61)			
Mobile Salary Treatment x Post x Salary Problem		10280.70		
		(7050.87)		
Mobile Salary Treatment x Post x Low Salary Satisfaction			963.97	
			(3972.70)	
Mobile Salary Treatment x Post x Low Government Control				247.48
				(2546.57)
Sample	All	All	All	All
Mean Dep Var	3153.96	3148.75	3137.30	3318.91
# Employees	334	334	334	332
# Observations	1418	1410	1412	1326
R-Squared	0.11	0.15	0.11	0.11
Month FE	YES	YES	YES	YES
Strata FE	-	-	-	-
Employee FE	YES	YES	YES	YES

Notes: Dependent variable is the M-Paisa mobile money account balance in columns (1)-(4). Observation is an employee-month. Average exchange rate was approximately 50 Afghanis to the dollar during study period. Standard errors clustered at the employee level in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The Expects Violence subgroups correspond to responses to the question "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood. Is this extremely likely, very likely, somewhat likely, not very likely, or extremely unlikely?" Extremely likely and very likely are coded as Expects Violence. Regressions include month and employee fixed effects as noted. Strata include provinces, share of income transferred to family (above/below median), and level of monthly expenditures on mobile airtime (above/below median). Trimming top .5% of outliers in cash savings.

Table A12: Experimental Dataset: Violence Expectations and Other Economic Responses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A	Bank Savings (Afs)								
Mobile Salary Treatment x Post	-5040.08	-5307.68	-5307.11	-2879.83	-2644.39	-4521.20			
	(3690.15)	(3705.70)	(3673.15)	(4075.60)	(4073.44)	(3804.24)			
Mobile Salary Treatment x Post x Expects Violence				-6502.16	-8355.72	-3068.25			
				(8313.76)	(8629.98)	(7903.39)			
Expects Violence (=1)				1698.93	640.22	3710.01	2282.80	1487.54	2339.38
				(2725.36)	(2924.07)	(3611.08)	(1655.52)	(1608.31)	(2023.76)
Mean Dep Var	3048.16	3048.16	3048.16	3048.16	3048.16	3048.16	3048.16	3048.16	3048.16
R-Squared	0.01	0.03	0.17	0.01	0.03	0.17	0.00	0.02	0.16
Panel B	Transfers (Afs)								
Mobile Salary Treatment x Post	611.17	391.16	1600.57	-921.93	-908.41	-562.45			
	(2040.34)	(1943.68)	(1951.06)	(2483.81)	(2331.06)	(2142.79)			
Mobile Salary Treatment x Post x Expects Violence				3356.70	3291.33	5798.26			
				(4985.95)	(4882.23)	(5013.54)			
Expects Violence (=1)				5017.49	3681.68	2764.24	2323.09*	2150.84*	1078.29
				(3644.97)	(3416.03)	(2972.61)	(1217.69)	(1258.20)	(1225.70)
Mean Dep Var	7379.55	7379.55	7379.55	7379.55	7379.55	7379.55	7379.55	7379.55	7379.55
R-Squared	0.02	0.11	0.44	0.02	0.11	0.44	0.01	0.09	0.43
Panel C	Expenditure (Afs)								
Mobile Salary Treatment x Post	3302.49	3426.33	3928.35	3322.78	3314.64	5164.80			
	(3290.58)	(3345.64)	(3299.35)	(4655.21)	(4487.47)	(4418.51)			
Mobile Salary Treatment x Post x Expects Violence				-4327.17	-2750.92	-6386.33			
				(8875.31)	(8150.59)	(7818.59)			
Expects Violence (=1)				2548.56	1050.34	-62.46	2204.13	2478.61	1688.42
				(5762.73)	(5617.00)	(5165.21)	(1670.24)	(1586.34)	(1617.34)
Mean Dep Var	23395.44	23395.44	23395.44	23395.44	23395.44	23395.44	23395.44	23395.44	23395.44
R-Squared	0.05	0.12	0.34	0.05	0.12	0.34	0.04	0.12	0.33
# Employees	315	315	315	315	315	315	315	315	315
# Observations	1236	1236	1236	1236	1236	1236	1236	1236	1236
Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Strata FE	NO	YES	-	NO	YES	-	NO	YES	-
Employee FE	NO	NO	YES	NO	NO	YES	NO	NO	YES

Notes: Dependent variable is self-reported bank deposits in Panel A, self-reported transfers in Panel B and self-reported expenditures in Panel C. All dependent variables are in Afghanis and observation is an employee-month. Average exchange rate was approximately 50 Afghanis to the dollar during study period. Standard errors clustered at the employee level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The Expects Violence subgroups correspond to responses to the question "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood. Is this extremely likely, very likely, somewhat likely, not very likely, or extremely unlikely?" Extremely likely and very likely are coded as Expects Violence. Trimming top .5% of outliers in cash savings, bank savings, transfers and expenditures.

Table A13: Experimental Dataset: Violence Expectations by Treatment Sample

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full Sample	M-Paisa Balance (Afs)			Cash Savings (Afs)		
Expects Violence (=1)	-1249.57**	-1575.20**	-414.27	3904.36**	3239.70**	3620.30**
	(565.14)	(731.63)	(521.59)	(1602.01)	(1594.53)	(1596.17)
Sample	All	All	All	All	All	All
Mean Dep Var	3247.91	3247.91	3247.91	5014.36	5014.36	5014.36
# Employees	333	333	333	333	333	333
# Observations	1341	1341	1341	1341	1341	1341
R-Squared	0.03	0.13	0.42	0.01	0.09	0.46
Panel B: Treat x Post Only	M-Paisa Balance (Afs)			Cash Savings (Afs)		
Expects Violence (=1)	-3632.34***	-3656.27**	-3200.52**	4768.43*	3689.09	2346.99
	(1374.33)	(1523.20)	(1396.06)	(2576.74)	(2782.62)	(2415.46)
Sample	Treat x Post	Treat x Post	Treat x Post	Treat x Post	Treat x Post	Treat x Post
Mean Dep Var	7524.18	7524.18	7524.18	5617.90	5617.90	5617.90
# Employees	162	162	162	162	162	162
# Observations	553	553	553	553	553	553
R-Squared	0.05	0.25	0.48	0.01	0.15	0.62
Panel C: Control Group Only	M-Paisa Balance (Afs)			Cash Savings (Afs)		
Expects Violence (=1)	234.62	394.61	388.58	3755.79	3197.99	4700.97*
	(239.33)	(360.46)	(382.46)	(2462.83)	(2520.90)	(2574.58)
Sample	Control	Control	Control	Control	Control	Control
Mean Dep Var	296.96	296.96	296.96	4618.86	4618.86	4618.86
# Employees	166	166	166	166	166	166
# Observations	646	646	646	646	646	646
R-Squared	0.00	0.12	0.30	0.00	0.04	0.41
Month FE	YES	YES	YES	YES	YES	YES
Strata FE	NO	YES	-	NO	YES	-
Employee FE	NO	NO	YES	NO	NO	YES

Notes: See Table 4 notes; sample in columns (1)-(3) is restricted here to match the estimation sample from columns (4)-(6).

Table A14: Experimental Dataset: Effect of Violence on Days to M-Paisa Withdrawal

	(1)	(2)	(3)	(4)	(5)
	Days to M-Paisa Withdrawal				
Expects Violence (=1)	-1.17**	-1.05**	-1.19***	-1.17***	-1.29**
	(0.46)	(0.42)	(0.45)	(0.41)	(0.56)
Sample	Treat x Post	Treat x Post	Treat x Post	Treat x Post	Treat x Post
Mean Dep Var	3.22	3.22	3.22	3.22	3.22
# Employees	162	162	162	162	162
# Observations	580	580	580	580	580
R-Squared	0.01	0.04	0.06	0.21	0.07
Month FE	NO	YES	YES	YES	YES
Province FE	NO	NO	YES	-	-
Strata FE	NO	NO	NO	YES	-
Employee FE	NO	NO	NO	NO	YES

Dependent variable is the number of days between salary deposit and first subsequent withdrawal in the M-Paisa mobile money account, and observation is an employee-month. Standard errors clustered at the employee level in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The Expects Violence subgroups correspond to responses to the question "In your opinion, please tell us how likely you think it is that insurgent-related violence will occur in your neighborhood. Is this extremely likely, very likely, somewhat likely, not very likely, or extremely unlikely?" Extremely likely and very likely are coded as Expects Violence. Regressions include month, province, strata and employee fixed effects as noted. Strata include provinces, share of income transfered to family (above/below median), and level of monthly expenditures on mobile airtime (above/below median). Trimming top .5% of outliers in cash holdings.

Table A15: Household Survey Dataset: Violence and Cash Savings Robustness

Dependent Variable:	Cash Savings (Afs)				
	(1)	(2)	(3)	(4)	(5)
Attacks (=1)	105.48		110.12	142.14	172.92
	(131.52)		(130.73)	(133.62)	(201.75)
Expects Violence (=1)		229.40*	232.04*	265.92*	176.34
		(121.70)	(121.36)	(160.42)	(198.26)
Attacks x Expects				-82.51	96.36
				(239.92)	(374.16)
Constant	375.74*	335.48	300.68	285.61	485.59*
	(199.69)	(204.11)	(203.75)	(211.20)	(271.10)
Sample	Trimmed	Trimmed	Trimmed	Trimmed	All
Mean Dep Var	862.38	862.38	862.38	862.38	960.59
# Clusters	287	287	287	287	287
# Observations	1122	1122	1122	1122	1127
R-Squared	0.141	0.143	0.143	0.144	0.098
Demographic Controls	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES

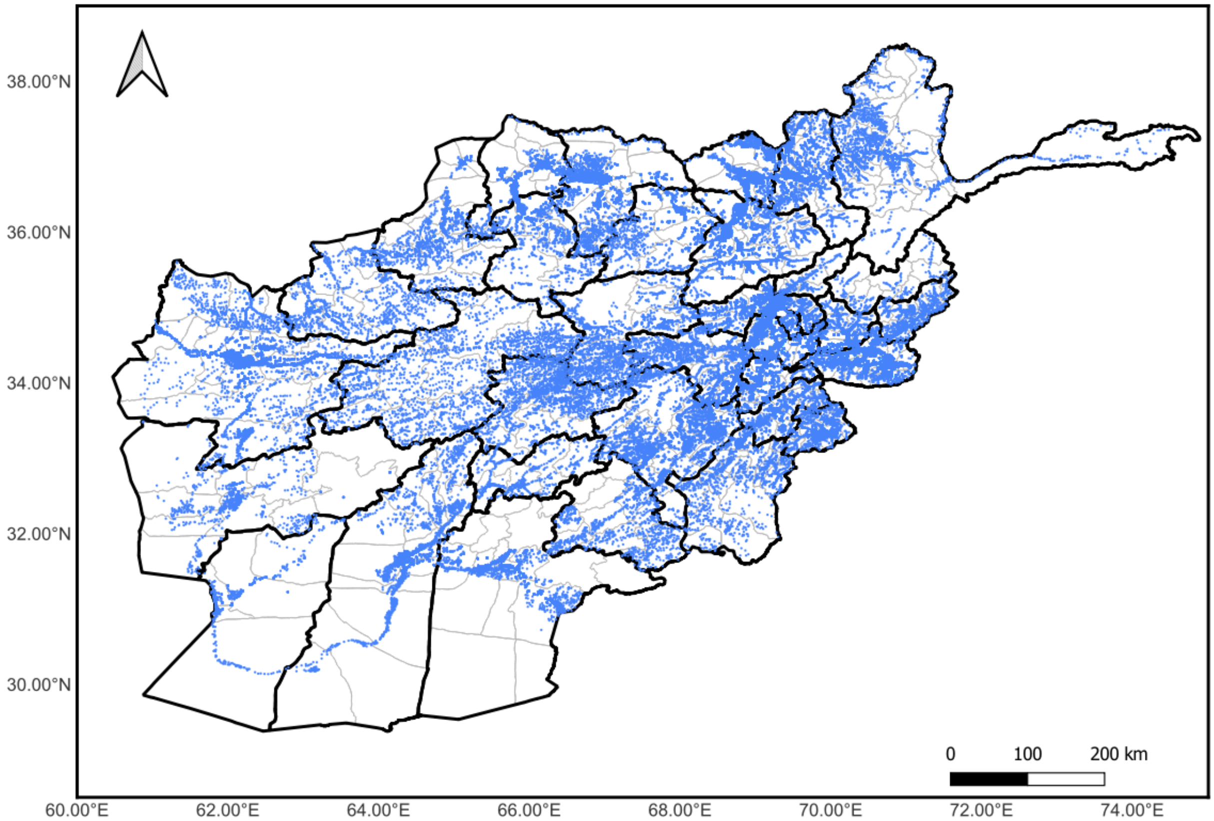
Notes: See Table 5 notes. Restricting estimation sample here to correpond with estimation sample in columns 1-4 of Table 6.

Table A16: Household Survey Dataset: Violence and Cash Savings - Additional Robustness

Dependent Variable:	Cash Savings (Afs)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Expects Violence (=1)	321.56*	331.24*	339.92*	349.33*	337.26*	320.90*	283.87
	(185.43)	(187.09)	(185.90)	(184.44)	(184.97)	(187.33)	(188.02)
Monthly Discount Factor	-3705.45					-4135.38	-4082.08
	(2343.87)					(3002.02)	(3048.89)
Present-Bias Paramenter		-2818.52				637.57	761.05
		(2825.38)				(3626.19)	(3584.23)
Ladder of Life (0-10)			10.26			10.77	14.30
			(42.76)			(42.25)	(41.15)
Financial Risk Likert (0-10)				58.67		52.87	11.75
				(46.99)		(45.80)	(44.98)
Holt-Laury Risk Measure					736.22*	692.21*	90.37
					(393.09)	(377.71)	(421.16)
Financial Risk Likert (0-10)							0.00
							(.)
Constant	4249.40*	3521.04	743.31***	664.37***	371.38*	3477.68	3407.36
	(2201.28)	(2750.54)	(200.81)	(120.80)	(223.41)	(2752.22)	(2748.00)
# Clusters	286	286	286	286	286	286	286
# Observations	972	972	972	972	972	972	972
R-Squared	0.378	0.375	0.374	0.377	0.378	0.385	0.406
Demographic Controls	NO	NO	NO	NO	NO	NO	YES
Polling Center FE	YES	YES	YES	YES	YES	YES	YES

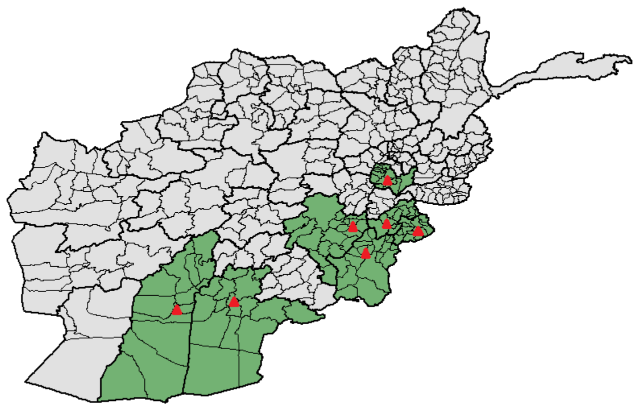
Notes: See Table 6 notes. Restricting estimation sample in columns 1-4 to correspond with estimation sample in columns 5-7.

Figure A1: Daily Locations – using Village closest to COG (Dec 2010 - April 2012)



Notes: Figure plots the estimated daily location for each M-Paisa user in the sample over the period December 2010-April 2012. The location is estimated using the village that is closest to the estimated Center of Gravity. Refer to Appendix A for a description of the Center of Gravity estimation methodology.

Figure A2: Experimental Dataset: CADG Provincial Office Locations (2012)



Notes: Experimental sample included 341 CADG employees operating in seven provinces (Ghazni, Helmand, Kabul, Kandahar, Khost, Paktia and Paktika) that are shaded in green, with office locations in provincial capitals marked with red triangles.

A2 Data Appendix

A2.1 Administrative Data

A2.1.1 M-Paisa transaction records

The M-Paisa transaction records cover the universe of all transactions conducted on Afghanistan's primary mobile money network from its launch in November 2008 until December 2013. We observe detailed information on each deposit, withdrawal, purchase, and peer-to-peer transfer. We use these transaction histories to calculate each subscriber's daily "Cumulative Balance," a running total of the total daily value stored on each subscriber's account.[41]

[41] Due to data recovery issues, we are missing all transaction records associated with 24 days of M-Paisa data. As cumulative account balances are calculated by aggregating over the entire transaction history, these missing data days create the potential for extreme positive and negative balances. We address this potential source of bias in our analysis by trimming the top 1% and bottom 1% of users by cumulative balance.

A2.1.2 Violent incidents in Afghanistan

We integrate violence incident records covering the period December 2010 to April 2012 from the International Security Assistance Force, a multilateral military body present in Afghanistan since December 2001. In all, there are more than 96,000 recorded incidents within our period of study. In addition to geocodes at 5 decimal digit precision (accurate to within one meter at the equator), these data provide the time and categorization of the incident. In effect, these data capture all types of violence reported to the International Security Assistance Force by military, diplomatic, aid and non-governmental sources, including incidents in which the force was not directly engaged. For our analysis we identify three types of incidents: direct fire, indirect fire, and IED explosions. Direct fire refers to attacks on a target that is visible to the attacker. Examples include small arms fire, rocket propelled grenades, or a thrown hand grenade. Indirect fire refers to attacks where the attacker fires from a distance and beyond line-of-sight and include artillery, mortars and rockets (NATO, 2016).

For our main analysis, we combine the three types of incidents in the empirical analysis, and attach each incident to any individual within a 10-kilometer halo. That is, if an incident is further than 10 kilometers from any individual's location it will not be used in the analysis and if an incident lies within 10-kilometer of two individuals, it will be attached to both of them. We define an indicator variable for violence exposure that equals one on a given day if at least one attack occurs in the 10-kilometer halo of that subscriber's location.

A2.1.3 Physical locations, extracted from call detail records

Finally, to determine which M-Paisa subscribers are likely to have been affected by each violent event, we calculate each subscriber's "Center of Gravity" for every day on which they are active on the mobile phone network. While M-Paisa transactions are not labeled with geographic locations, each time a subscriber sends or receives a phone call or text message the network operator logs the cellular tower closest to the subscriber at the moment the call was initiated. We extract all such tower information for each M-Paisa subscriber and, as is discussed in greater detail in Blumenstock (2012), we use this information to estimate the center of gravity COG_{it} of individual i at time t as

$$COG_{it} = \frac{1}{N_{it}} \sum_{s=T_{min}}^{T_{max}} K(\frac{t-s}{h}) \cdot \widehat{q_{is}}$$

where N_{it} is the total number of phone calls made by i within a window of time $[T_{min}, T_{max}]$ symmetric around t, and $\widehat{q_{is}}$ is the (known) location of the tower used at time s. The kernel $K(x)$ is a symmetric function that integrates to one, which specifies the extent to which additional weight is placed on calls close in time to t. The smoothing parameter $h > 0$ controls the bias and variance of the estimator. In our results we use a uniform kernel such that $K(u) = 1/N_i$. In cases when an individual makes no calls for a period of time, we impute the location by assuming that the individual is in the location of their last call until we observe them again. However, our results are robust when the analysis is restricted to non-imputed locations (Appendix Table A7).

A2.1.4 ANQAR survey

The Afghanistan Nationwide Quarterly Assessment Research (ANQAR) is a nationally representative survey of Afghanistan that includes respondents from all 34 provinces. The survey is conducted quarterly through face-to-face interviews. Surveyed respondents are 18 years of age or older and include both males and females. The primary purpose of the survey is to record general attitudes, beliefs, and issues that are important to Afghan people. Refer to Plumb et al. (2017), Condra et al. (2018), and Sonin and Wright (2020) for more details on ANQAR.

For our analysis, we focus on ANQAR waves that (i) match our period of study, and (ii) contain uniform questions across waves. Waves 11 to 15 match these two conditions. We aggregate the responses to the district-month level. In all, we obtain repeated cross-sections for 188 districts (398 districts in Afghanistan, 239 districts in our main estimation sample) with 7 months each (March, June, September, November, December 2011 and February, March 2012). We construct the following variables at the district-month level: average age; share of females; share of rural population; share of population with primary, and secondary education; share of population receiving income from farming; average number of hours per day with electricity; share of the population that is Pashtun. We proceed by merging these variables with our original estimation sample and include these district-level variables as additional controls in our estimation of Equation (2).