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

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**Abstract**

We examine the relationship between violence and financial decisions in Afghanistan. Using three separate data sources, we find that individuals experiencing violence retain more cash and are less likely to adopt and use mobile money, a new financial technology. We first combine detailed information on the entire universe of mobile money transactions in Afghanistan with administrative records for all violent incidents recorded by international forces, and find a negative relationship between violence and mobile money use. Second, in the context of a randomized control trial, violence is associated with decreased mobile money use and greater cash balances. Third, in financial survey data from nineteen of Afghanistan's 34 provinces, we find that individuals experiencing violence hold more cash. Collectively, the evidence indicates that individuals experiencing violence prefer cash to mobile money. More speculatively, it appears that this is principally because of concerns about future violence. The degree of the relationship between cash holdings and violence is large enough to suggest that robust formal financial networks face severe challenges developing in conflict environments.

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# 1 Introduction

Many poor countries are plagued by violence.[1] While a substantial literature documents the positive relationship between poverty and conflict, economists have only recently begun to explore the micro-economic mechanisms linking violence to economic stagnation and low levels of income.[2] Conflict destroys capital (Davis and Weinstein, 2002; Miguel and Roland, 2011), deters investment (Besley and Mueller, 2012; Singh, 2013), changes economic decision-making (Voors et al., 2012; Callen et al., 2014), and introduces additional uncertainty about the future. Due in part to a lack of reliable data, the impact of violence on financial decisions is not well understood.

This paper studies the relationship between violence and financial decision-making. We pursue this using data for the universe of mobile money transactions, precise approximations of mobile money users physical locations based on their geo-tagged call records, administrative records for all violent incidents recorded by international forces, a cross-section of financial survey data from nineteen of Afghanistan's 34 provinces, and monthly panel data from an experiment that strongly incentivized mobile money adoption. The combination of sources allow us to examine the financial responses to violence in two separate large populations and with monthly financial survey data in an experimental sample. Collectively, these data provide a rare glimpse into financial behavior in several samples that are both affected by violence and in the midst of adopting a major new financial technology.

The analysis provides three central findings. First, violence is associated with lower mobile money balances and fewer transactions both for subjects in our experiment and for mobile money users in general. Related to this, our experimental intervention involved paying subjects their entire salary using mobile money, providing a sharp incentive to use mobile money. Treatment subjects that experience violence keep roughly half as much of their salary

[1]Approximately 1.5 billion individuals (roughly 20% of the world population) live in countries affected by fragility, violence or conflict (World Bank, 2011).

[2]Blattman and Miguel (2010) and Mueller (2013) provide excellent reviews of the economic causes and consequences of civil conflict.

as mobile balances compared to treatment subjects unaffected by violence. Second, violence is associated with an increase in cash holdings that is roughly proportional to the reduction in mobile money balances both for subjects in our study and for subjects in the nineteen province sample. Last, respondents who think that future violence is more likely exhibit less mobile money usage and higher cash savings in both the nineteen provinces and in the experimental sample. These relations remain significant, in the latter sample, using only within-subject variation and controlling for any time-invariant individual-specific factors.[3]

Our non-experimental results are based on an analysis of the complete history of transactions made on the M-Paisa mobile money network from its creation in 2008 until 2013.[4] We combine this rich administrative dataset with a geocoded database of tens of thousands of violent events in Afghanistan. In our population of regular M-Paisa users, we find that the individuals who are more exposed to violence are less likely to use the mobile money system as a storage of value or a means of exchange. This finding persists even when controlling for unobserved heterogeneity at the individual level: the same individual is less likely to use mobile money in the immediate aftermath of violent events.

To better understand why violence impacts the adoption and use of mobile money, we conduct a field experiment in Afghanistan in which we induce random variation to an individual's propensity to adopt mobile money. In our 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. To ensure consistency across treatment and control groups, all employees received new phones and were enrolled for accounts on the mobile money platform and trained in how to use the new technology. Despite being able to fully cash out their mobile salary deposits, the treatment group shows significant increases in usage of their mobile account, but both exposure to violence and

[3]In results available on request, estimates including province by month fixed effects produce similar results, at least partly controlling for changes in the objective risk of violence experienced by employees in the same province.

[4]In this version of the paper, we limit our analysis to the Dec 2010-April 2012 period where we can currently match M-Paisa users to geolocations using calling records.

expectations of future violence mute these effects. We show that subjects who believe that future violence is more likely hold lower mobile money balances and keep more cash, even when facing identical objective levels of risk.

Moreover, the panel survey data collected in the experiment provides suggestive evidence for the mechanism by which violence attenuates an individual's use of mobile money. Namely, we observe that instead of saving money in their mobile accounts, individuals with greater expectations of future violence are more likely to retain cash on hand. This finding is corroborated by a nationwide household survey data from Afghanistan, in which we observe a strong positive correlation between an individual's subjective expectations of future violence and the amount he saves in cash relative to other technologies. We are also able to rule out several possible alternative explanations, for instance that our effect is driven by increases in transaction and travel costs or by potential reductions in agent liquidity.[5]

Individuals experiencing (and expecting) violence in Afghanistan appear to prefer cash to mobile money. This is in line with observations about the limited development of formal banking services in the country; only 9% of Afghan adults to hold bank accounts and only 3% to save money at a financial institutions (Demirguc-Kunt and Klapper, 2012). The development of financial systems requires broad participation and long time horizons from account holders. This is likely to be particularly true for mobile money, which provides a prototypical example of a technology subject to network externalities (Mas and Radcliffe, 2011). A range of advocates see in mobile money the opportunity to build a new financial system that does not require the brick-and-mortar investment of a bank-based financial system (Dermish et al., 2011; Mbiti and Weil, 2011; Suri et al., 2012). But while we document demand from Afghan firms for paying employee salaries using mobile money, our results suggest that individual users will continue to be reluctant to use the financial technology as long as violence is part of their daily lives.

Our findings complement a growing body of literature attempting to understand the

[5] As we document that individuals decrease their mobile money balance following violent events, it is unlikely that the agents are unable to provide withdrawals specifically due to these violent events.

economic impacts of mobile phones and other information and communications technologies in developing countries. Beginnining with work by Jensen (2007) and Aker (2010), the mass proliferation of mobile phones has been linked to increased efficiency in agricultural markets. More recent work by Jack and Suri (2014) and Blumenstock et al. (2014) further indicates that mobile money can reduce transaction costs in remittances and help enable more efficient risk sharing. In work closest to our own, Aker et al. (2011) show that mobile money payments can reduce inefficiencies for both the payer and payee. Our focus, however, is different. While we find complementary evidence that mobile money salary payments create efficiencies for the employer, we find that the benefits to employees are not uniform. In particular, our analysis of the detailed mobile money transaction records allows us to examine how different types of individuals, and in particular those exposed to violence, use the technology differently from the average subscriber.

The remainder of the paper is structured as follows. The next section reviews the setting and provides institutional details. Section 3 provides initial evidence on the relationship between violence and mobile money adoption from two large administrative datasets from Afghanistan during 2010-2012. Section 4 presents further evidence from the randomized experiment conducted in Afghanistan during 2012-2013. Section 5 examines underlying mechanisms, and Section 6 concludes.

# 2 Violence and Financial Development in Afghanistan

## 2.1 Violence in Afghanistan

Afghanistan is one of the world's poorest and most-conflict affected countries. Beginning with a communist coup in 1978 and the Soviet invasion in 1979, the country has endured almost three and a half decades of civil conflict. After US and NATO military forces began operations to defeat the Taliban regime in October 2001, the new Afghan government has 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 as the Taliban insurgency gained strength starting in 2006, the civilian population's exposure to violence has continued to be a major issue. The United Nations estimates that during the six years from 2007 to 2012, over 14,500 civilians lost their lives in the armed conflict, including over 2,750 civilian deaths in 2012 alone. Approximately 80% of civilian casualities in 2012 were attributed to the insurgency, including a rise in both targetted killings and the indiscriminate use of improvised explosive devices (United Nations 2013). As shown in Figure 1, recent violence has been particularly concentrated in the south and east of the country along the border with Pakistan where the insurgency is based.

## 2.2 Financial Development in Afghanistan

Afghanistan's number of commercial bank branches per 100,000 adults is approximately 2%, which is less than a quarter of the South Asia regional average of 8% (IMF 2011). 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 goverment salaries each month, further shook confidence in the formal financial system (Filkins, 2011). With only 3% of Afghans saving with a formal bank account, most rely on cash holdings and other informal savings vehicles (Demirguc-Kunt and Klapper, 2012). The money exchange network of hawala brokers offers an parallel system for domestic and international payments, with limited funtionality 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 has grown rapidly over the past decade, from approximately 25,000 subscribers in 2002 to over 18 million subscribers in 2012 (World Bank 2014). 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. This period also marked a concentrated effort to significantly expand agent coverage outside of Kabul to include other major population centers such as Herat, Mazar, Jalalabad, Helmand and Kandahar. In early 2012, Roshan's competitor Etisalat launched its own mobile money service, M-Hawala, and the remaining mobile operators have expressed plans to follow.

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 enjoys 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. However, brand recognition and trust in major mobile operators such as Roshan continues to grow, alongside efforts to expand the coverage of mobile money agents and increase the number of channels willing to accept mobile money as a means of exchange. One noteworthy feature of mobile money in Afghanistan is that government regulations require mobile operators to maintain regular deposits in local banks equal to the entire value held on their mobile money system, creating a significant connection between mobile money

[6]Four major mobile operators compete in Afghanistan: Afghan Wireless Communications Company (AWCC), Etislat, 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).

users and the existing financial system.

Mobile money adoption in Afghanistan is best understood in the broader context of the global adoption of mobile money. Launched in 2007, the most successful and well-known deployment of mobile money in the developing world has been Safaricom's M-PESA platform in Kenya, which is used by approximately 17 million Kenyans (over two-thirds of the population) and carries approximately 25% of the country's gross national product (Economist 2013). As of late 2013, over two hundred mobile money deployments were active in 80 developing countries, with approximately two-thirds being launched in the past three years (GSMA 2014). But despite some notable exceptions such as MTN Uganda, Vodacom Tanzania, FNB in South Africa, and GCASH and Smart Money in the Phillipines, global mobile money adoption has struggled to match the impressive growth rate of Safaricom's M-PESA. In 2012, only six mobile money platforms had more than 1 million active customers - three of which crossed that threshold during that year (GSMA 2013). According to World Bank figures, approximately 16% of adults in Sub-Saharan Africa report having used a mobile phone to pay bills or send or receive money over the past year, though much of that mass is concentrated in the successful East African deployments.[7] In Afghanistan, almost 7% of adults report using a mobile phone to receive money and 3% report sending money by mobile phone (Demirguc-Kunt and Klapper, 2012).

## 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.[8] In the particular case of mobile salary payments - wage transfers made by an employer to an employee using mobile money - large firms are able to instaneously complete individual financial transfers to their employees. Individual users are notified of

[7] For example, there are now more mobile money accounts than bank accounts in Kenya, Madagascar, Tanzania and Uganda (GSMA 2013).

[8] Illiterate users can also access the M-Paisa platform using an interactive voice response (IVR) system.

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. 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. Individuals users can maintain a balance on their mobile money account, providing them with a storage of value functionality.[9] Individual users also can 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.[10]

# 3 Violence and Mobile Money: Results from Administrative Data

Our primary focus is on understanding the effect of violence on an financial decision-making in Afghanistan. We begin by providing robust evidence that exposure to violence decreases the likelihood that an individual will use, and store balance in, his M-Paisa mobile money account. To do this, we create a novel dataset that combines the complete history of M-Paisa transactions over a 6-year period with administrative records of all violent incidents recorded by international forces in Afghanistan. To join these datasets and determine each M-Paisa subscriber's exposure to violence over time, we have worked with Afghanistan's primary

[9]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 maxium balance limits on mobile money accounts.

[10]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.

mobile phone operator to obtain the complete anonymized and geo-tagged mobile phone call records of each M-Paisa user, which allows us to approximately locate each individual user on every day for which we have data.

Using methods described in greater detail in Appendix A, we create a balanced panel of data that captures, for each individual $i$ in each time period $t$, several different 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", a weighted centroid of the locations from which he is known to make or receive phone calls, which provides an approximate location $COG_{it}$ for each individual in each time 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.

$$Violence_{it} = \mathbb{1}\left[\sum_{v_{lr}} 1 > 0\right], \forall v_{lt} \text{ s.t. } distance(COG_{it}, v_{lt}) < R$$

Given this balanced panel, we estimate the impact of violence on M-Paisa use with a regression model that includes individual fixed effects $\pi_i$, district fixed effects $\eta_d$ and time fixed effects $\mu_t$.

$$Y_{it} = \beta Violence_{it} + \pi_i + \eta_d + \mu_t + \epsilon_{it} \tag{1}$$

The results we present below use a specification that attaches each violent incident to any individual within a 10 kilometer radius, i.e. $R = 10$, but Appendix Table A1 shows that our estimates are robust to a wide range of plausible values for $R$. We aggregate events and transactions at the weekly level, though again our results are robust to different levels of temporal aggregation. We will further focus attention on specific population of M-Paisa users who we consider most relevant for policy analysis: (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.[11] These restrictions limit our sample to a total of 7,784 individual salary users during the period from December 2010 to April 2012.

### 3.1 Results

Using these administrative data, we find a strong negative relationship between violence exposure and M-Paisa usage. Table 1 presents the results from the fixed-effect specification in Equation 1, and is identified based on within-individual changes over time. In other words, on average, individuals exposed to violence significantly reduce their M-Paisa balance during periods of heightened violence (column 1). More precisely, exposure to violence is associated with a decrease in a user's average daily M-Paisa balance of 259 Afghanis (approximately $5 USD), which is 12% of the mean value of the dependent variable.

Columns (2) - (6) of Table 1 indicate violence has similar effects on the extensive margin of M-Paisa use: violence is associated with a reduction in activity in all of the most common M-Paisa transaction types, including deposits, withdrawals, and peer-to-peer transfers. Column (3) shows the coefficient on the violence indicator for withdrawals is 9% of the mean of the dependent variable, while columns (4)-(6) show related effect sizes of 62% on deposits, 9% on airtime purchases, and 22% on peer-to-peer transfers.

The negative correlation between violence and M-Paisa use also exists in the cross section, such that individuals located in violent areas are also less likely to use M-Paisa. These results are presented in Appendix Table A2, where we estimate variants of Equation 1 with and without a variety of fixed effects. However, since a large number of omitted variables could reasonably account for the observed correlation between violence and M-Paisa use, we find these results less straightforward to interpret.

[11] As shown in Appendix Table A3, our estimates are qualitatively similar when we relax the latter assumption to include non-salary users.

# 4 Violence and Mobile Money: Experimental Results

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

To address these econometric concerns and better understand the impact of violence on a wider range of financial decisions, we conduct a randomized control trial in Afghanistan in which we induce random variation to an individual's propensity to adopt mobile money. In our experiment, employees of a large, Afghan-staffed firm operating in some of the most violent areas of the country were randomly assigned to receive their monthly salary payments in mobile money or remain in the status quo cash payment system. We combine detailed administrative transaction records with monthly survey data on both the treatment and control group to achieve a more detailed understanding of the mechanisms underlying the individual decisions to reduce usage of M-Paisa.

## 4.1 Research Partner

Headquartered in Singapore, the Central Asia Development Group (CADG) is a private contractor that delivers engineering, aviation, agricultural services and development assistance to remote and challenging locations. In Afghanistan, CADG's flagship development initiative has been a USAID-supported Community Development Program (CDP), primarily based in the conflict-affected southern and eastern provinces of the country. 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. In 2011, a small number of CADG's CDP staff in Kabul and Kandahar entered a pilot of Roshan's mobile salary payment program on the M-Paisa platform. Salaries were authorized directly from CADG's Singapore headquarters using an online interface and delivered monthly to the participating employees' mobile phones via SMS notification. In mid-2012, the firm decided to scale up its use of mobile salary payments in the CDP program, and agreed to a randomized experiment to study the effects on its employees.

## 4.2 Protocol

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 research study was launched in August 2012 with a randomized experiment involving 341 CDP employees operating in seven provinces: Ghazni, Helmand, Kabul, Kandahar, Khost, Paktia and Paktika (see Figure 2).[12] 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.[13] The experimental sample included all CDP employees who worked in office locations with Roshan mobile coverage, and excluded the CDP security staff who were being transitioned to an alternative payment system under the Afghan Public Protection Force (APPF). Half of the employees in the experiment were randomly assigned to the mobile salary system, while the other half were paid by CADGs existing cash-based system

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

[13] We also consistenly 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.

to provide a valid comparison group during the study period. A single treatment arm was selected to make full use of the employee sample, to ensure compliance with the experimental design, and to isolate the causal effect of mobile salary payments from associated treatments involving training, distribution of phones and registration for mobile money.

Employees in the control group receive a basket of interventions that closely resemble those received by the employees in the treatment group. Both sets of employees receive 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 are distributed new phones, which are identified as their new official work phones, and both sets of employees are given Roshan SIM cards, which are 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 are 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. 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 included two further blocking variables: the share of monthly income transferred to a family, and the level of monthly expenditure on phone airtime. In both cases, the variable's distribution was divided into above and below the median, and the stratification was implemented using that definition. 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 Pakita and Paktika received regular in-person visits from an agent to their office in order to address security concerns specific to those two provinces.[14]

To address the logistical challenges of travelling 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 takes 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.[15] We thus create an unbalanced monthly panel of employees in which provincial offices are enrolled in different months, but then experience a similar monitoring regime in relative time.

### 4.3 Take-up

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.[16] Baseline administrative and survey data summarized in Table A4 indicates balance on employee observables such as age, marital status, number of children, ethnicity, tenure, salary, and usage of formal banks and hawala system.

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

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

[15]Paktia and Paktika province offices were 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.

[16]The randomization pool included additional employees who had their employement 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 salaries pilot project prior to the research study.

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 in response to the question “Has the neighborhood in which you currently live experienced an attack in the current calendar month (previous calendar month)?”, with approximately half of our sample answering affirmatively to this question at some point during study period. 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 $\text{Violence}_{it}$ that equals one if respondent $i$ answered either “extremely likely” or “very likely” in month $t$.[17] Additional monthly survey data reported in this table includes monthly cash savings, expenditures, bank savings and cash transfers to friends and family members.

## 4.4 Results

We begin by demonstrating increased usage of mobile money in the treatment group in columns (1) - (3) of Table 3, with large, positive and statistically effects on mobile money balances. We gradually introduce month fixed effects, strata fixed effects and employee fixed effects to show the robustness of our results to increasingly restrictive sources of variation. We aggregate our transaction data to the monthly level and estimate the following difference in differences specification, where the onset of treatment is defined as the date of the first mobile salary payment in a given province.

[17] 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.

$$Y_{it} = \text{Treat x Post}_{it} + \text{Treat}_i + \text{Post}_t + \gamma_t + \eta_i + \tau_i + \epsilon_{it} \tag{2}$$

In the above specification, $i$ indexes employees and $t$ indexes months. $Y_{it}$ is the outcome variable of interest, $\text{Treat}_i$ is a dummy variable that equals one for individuals randomly assigned to receive mobile salary payments, $\text{Post}_t$ is a dummy variable that equals one after the onset of treatment, Treat x $\text{Post}_{it}$ is a dummy variable that equals one if both $\text{Treat}_i$ and $\text{Post}_t$ equal one, $\gamma_t$ is a month fixed effect, $\eta_i$ is a strata fixed effect and $\tau_i$ is an employee fixed effect.

We next extend this regression framework to a triple-difference by including interactions with the Expects $\text{Violence}_{it}$ variable. As shown in columns (4) - (6) of Table 3, we find an average effect of the treatment on mobile savings balances during periods of high violence beliefs that is consistently negative in sign, large in magnitude and statistically significant. It is satisfying to note that the magnitude and significance of the estimated effects does not vary across these increasingly restrictive specifications, especially when limiting attention only to within-employee variation in column (6).[18]

Figure 3 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 significiantly different than zero during the period of the experimental study. By contrast, the M-Paisa balances in the treatment group are large and significantly different than zero, even after allowing for cash withdrawals immediately following each pay period. Figure 4 presents a corresponding graphical representation of the treatment effect on M-Paisa balances when broken down into violence subgroups, though here the violence groups are fixed over the full period for each individual by taking the average violence belief across all reported months. Again, we see strong evidence that violence expectations drives a faster exit from mobile money in our treatment sample.

[18]As Table A5 shows, our results in column (4)-(6) are qualitatively similar when separating the violence expecations variable into each answer, though grouping them improves power.

In Table 4, we show corresponding and opposite effects of violence expectations on self-reported cash savings. In columns (1) - (3) we show that there is no direct effect of treatment on cash savings. In columns (4) - (6) we then pool our treatment and control observations and examine the effect of violence expectations directly on cash savings without any treatment interaction. Again, it is noteworthy that the magnitude and statistical significance of our results to not change dramatically when including fixed effects for month, strata and individual employee. Given the organization of our data in a high-frequency panel, this relationship seems covincingly causal. It is noteworthy that the magnitude of the increase in cash savings observed in columns (4) - (6) of Table 4 is more than 80% of the decrease in mobile money savings seen demonstrated in the corresponding columns of Table 3. In Table 5 we show that our results are unique to cash savings; other economic measures such as bank savings, individual transfers and expenditure show no effect from increased violence expectations. In additional results presented in Table A6, we find that high violence beliefs are characterized by faster withdrawals immediately following pay day, consistent with this interpretation of switching from mobile savings to cash savings as expectations of future violence rise.

# 5 Mechanisms

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 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.[19] By this logic, violence should increase the relative demand for cash.

Countervailing against this, mobile money offers security advantages compared with cash.

[19] An exception to this is a small number of locations in Kabul directly accept mobile money as payment.

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 general, and mostly 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 drive tremendous migration, usually to Pakistan and Iran.[20] Mobile money users tend to be wealthier, especially in our CADG sample, and may be considering whether to leave Afghanistan after coalition troops withdraw at the end of 2014. 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 region demand much higher premia to transact mobile money than those in more stable regions. Mobile money operators refuse to operate altogether in highly unstable regions. An increase in violence might both increase the effective cost to withdraw mobile money and decrease the probability that it can with be withdrawn at all.[21]

## 5.1 Violence and Cash Savings in a Large Household Survey

We test the relationship between violence expectations and cash savings in an entirely separate sample from Afghanistan, as described by Callen et al. (2014). These data, collected in December 2010, reflect 468 different primary sampling units (elections polling centers) across nineteen provincial capitals. 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,

[20]According the United Nations High Commissioner for Refugees (UNHCR), since 2002, 3.8 million Afghans, about 12.75 percent of Afghanistan's total population, have repatriated from Pakistan alone. There remain roughly 1.6 million Afghan refugees in Pakistan, with numbers likely to swell in coming years (United Nations High Commissioner on Refugees, 2014).

[21]In additional results presented in Table A7, we find no evidence that violent events in a district directly affect the operation of the mobile network, but do find evidence that violence decreases the number of agents present in a district and conducting transactions by approximately 5%. In further analysis presented in Table A8, we find that our main experimental results are robust to including such time-varying confounds as household shocks, salary problems, salary satisfaction and expectations of future government control.

men and women were interviewed by field staff of their own gender. Three features of these data provide a means of testing whether our results might generalize beyond our experimental sample. First, they afford much greater spatial 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 in the data for the experiment.[22]

Table 6 presents results using the 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 INDURE database in a 1km radius of the polling center within the past 3 years).[23] 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. 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 insignificant 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.

## 5.2 What Does our Violence Expectations Variable Measure?

Our violence expectations question asks subjects to directly state their subjective beliefs that a particularly state of the world "insurgent-related violence will occurring in your neighborhood" will obtain. 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

[22]The only difference between these modules that the expectations elicitation question in 2010 used a ten point likert scale while in 2013 it used a five point scale.

[23]Reported results are robust to alternative radius specifications, as well as to the exclusion of demographic controls and province fixed effects.

a review of efforts to elicit subjective probabilities in developing countries, arguing that a 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.

A simple way to describe the objective of the question is to think of a basic two period model where payoffs are state-contingent. Imagine that an individual can consume a fraction $a$ of their salary $s$ and save a fraction $(1 - a)$ at an interest rate of $r$. They will save until the indifference condition $u(c_0 + as) + \delta E[u(c_1)] = u(c_0) + \delta E[u(c_1 + (1 + r)(1 - a)s)]$ is satisfied. Assume that, in the future period, they will survive with probability $p$ and that $u(0) = 0$. Then, the indifference condition simplifies to $u(c_0 + as) - u(c_0) = \delta p[u(c_1 + (1 + r)(1 - a)s) - u(c_1)]$. Using the implicit function theorem, it is straightforward to show that $\frac{\partial x}{\partial p} = \frac{\delta[u(c_1+(1+r)(1-a)s)-u(c_1)]}{u'(c_0+a)} > 0$. This provides a simple result, which obtains in a range of models. Ceteris paribus, increasing survival probabilities (or the probability that savings can be converted into consumption) should increase current savings. We designed this question, using insights from the literature on subjective elicitation, to provide a proxy for $p$.

In practice, this question could be correlated with a range of confounds including: (i) general optimism; (ii) risk aversion; (iii) discount factors; and (iv) present bias. Table A11 includes measures of each of these confounds as an additional regressor. 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 confounds.

# 6 Conclusion

Our data suggest that conflict substantially reduces the financial involvement of Afghans. Across three separate data sets, we find that violence-affected individuals hold substantially more cash. In some cases, these individuals hold twice as much cash as individuals who are not affected. At the same time, in our experiment, we find that violence is associated with a halving of the amount of mobile salaries kept as mobile money.

Financial networks and mobile money in particular exhibit network externalities. The value of a mobile money account depends on the number of people with whom a client can transact. Moreover, mobile money agents will not operate unless they achieve a certain volume of customers. The same is true of bank savings and electronic bank transfers, which are virtually nonexistent in Afghanistan. The magnitudes we find are large enough to suggest that violence poses a substantial barrier to the development of formal financial networks.

Subjects in our experiment provided a monthly panel of forecasts of violence. Using within-subject estimates, a one-standard deviation increase in forecasts is associated with holding 20% percent less mobile money and 20% percent more cash. Expectations also appear to have more explanatory power than actual violence exposure. This finding is corroborated in a separate sample using nationwide household survey data from Afghanistan, in which we observe a strong positive correlation between an individual's subjective perception of uncertainty and the amount he saves in cash relative to other technologies. Our empirical analysis also allows us to rule out several possible alternative explanations, for instance that our effect is driven by increases in transaction and travel costs or by reductions in agent liquidity coinciding with violent events.

The adoption failure we observe does not appear to be primarily about the effects of violence on the general economy, transaction costs or the mobile money system. Rather, it operates at the level of individual decisions. Our work highlights the importance of individual decision-making channels in understanding the economic consequences of violence, and suggests that the preference for cash which attends experience (and expecting) violence creates an obstacle to the develop of robust formal financial networks.

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# Tables and Figures

Figure 1: Violent Incidents in Afghanistan (Dec 2010 - April 2012)

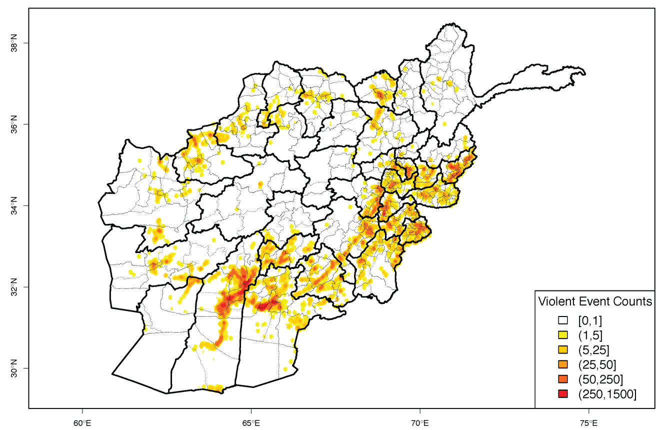


Figure 2: CADG Provincial Office Locations (2012)

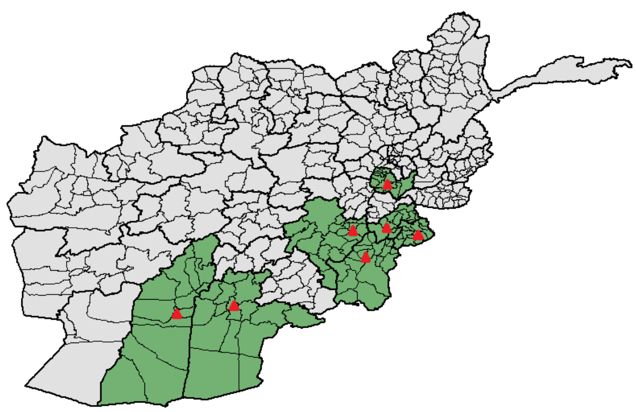

Figure 3: Treatment Effect on M-Paisa Balance

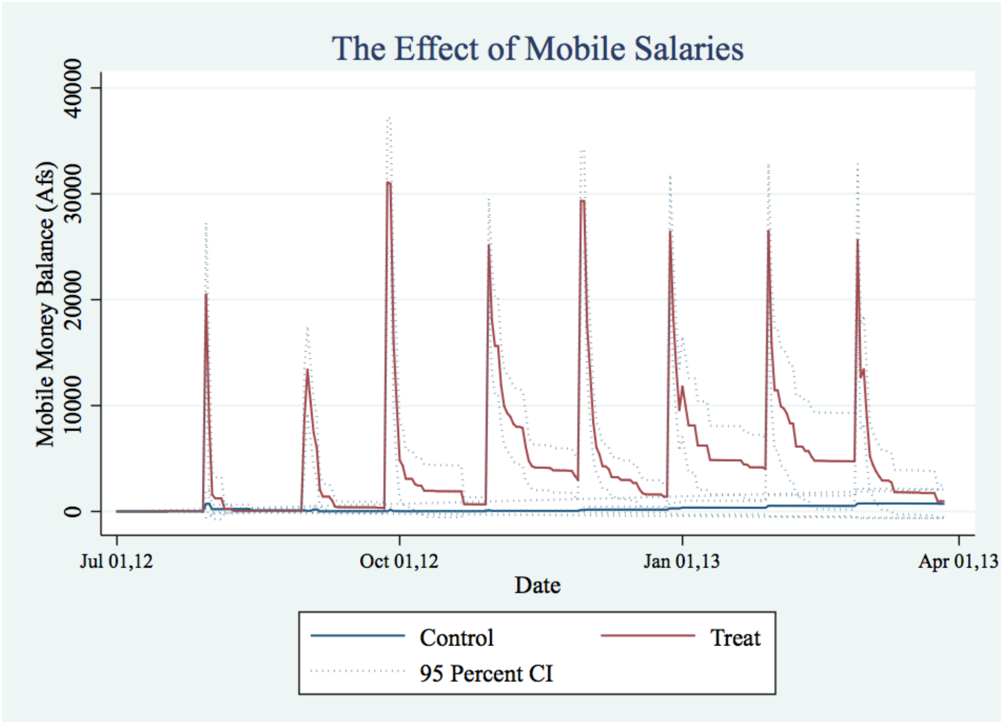


Figure 4: Treatment Effect on M-Paisa Balance By Violence

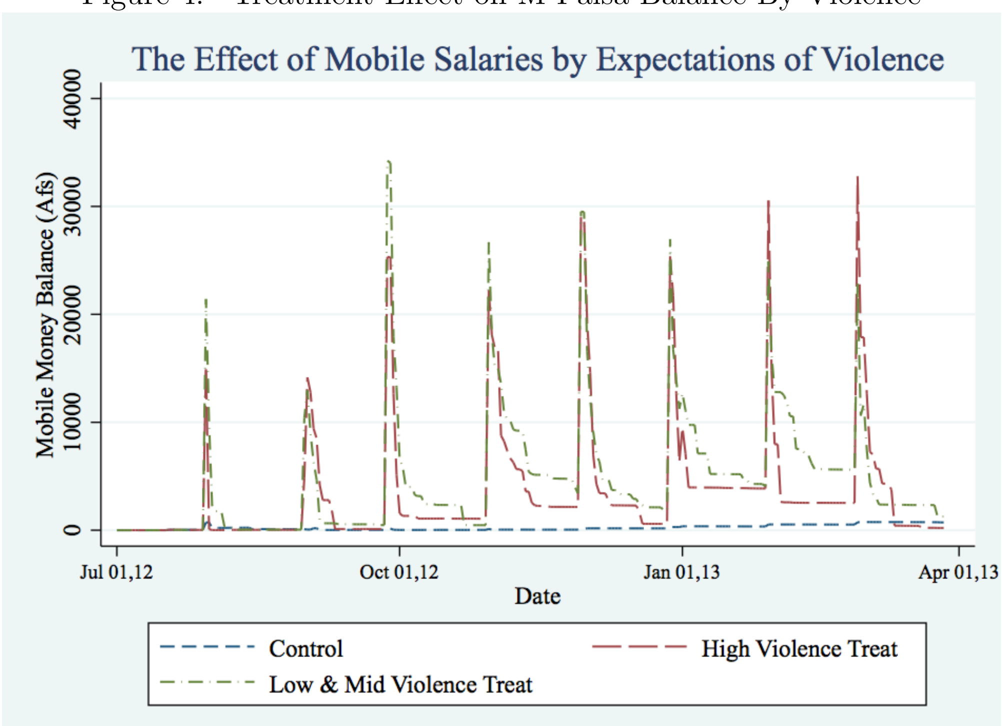

Table 1: Administrative Dataset: Violence and M-Paisa Use

| Dependent Var. | M-Paisa Balance | Transactions (#) | Withdrawals (#) | Deposits (#) | Airtime (#) | Send Money (#) |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Violent Event in 10 km (=1) | -259.08*** | -0.030*** | -0.007*** | -0.002*** | -0.004*** | -0.002*** |
| | (35.45) | (0.002) | (0.001) | (0.000) | (0.001) | (0.000) |
| Sample | Salary Users | Salary Users | Salary Users | Salary Users | Salary Users | Salary Users |
| Mean Dep Var | 2107.34 | 0.191 | 0.064 | 0.002 | 0.034 | 0.008 |
| # Individuals | 7784 | 7784 | 7784 | 7784 | 7784 | 7784 |
| # Observations | 314986 | 314986 | 314986 | 314986 | 314986 | 314986 |
| R-Squared | 0.62 | 0.29 | 0.18 | 0.11 | 0.38 | 0.17 |
| Week FE | YES | YES | YES | YES | YES | YES |
| District FE | YES | YES | YES | YES | YES | YES |
| Individual FE | YES | YES | YES | YES | YES | YES |

*Notes:* Dependent variable is the M-Paisa mobile money account balance in Afghanis in column (1), the number of M-Paisa transactions in column (2), the number of withdrawals in column (3), the number of deposits in column (4), the number of airtime purchases in column (5) and the number of peer-to-peer mobile money transfers in column (6). Observation is an individual-week. Violence variable is a dummy for whether a violent attack was recorded in the INDURE dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user. Robust standard errors, clustered at individual 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: Summary Statistics: Experimental Sample

| Variable | Mean | Std. Dev. | N |
|---|---|---|---|
| Treat (=1) | 0.502 | 0.5 | 2049 |
| *M-Paisa Usage:* | | | |
| M-Paisa Balance (Afs) | 3152.075 | 185337 | 2049 |
| Airtime (Afs) | 52.143 | 263.977 | 2049 |
| Transactions (#) | 1.515 | 2.229 | 2049 |
| Deposits (#) | 0 | 0.022 | 2049 |
| Deposits (Afs) | 0.244 | 11.046 | 2049 |
| Withdrawals (#) | 0.381 | 0.533 | 2049 |
| Withdrawals (Afs) | 11834.096 | 24344.253 | 2049 |
| Travel Time to M-Paisa Agent (minutes) | 91.435 | 70.336 | 1700 |
| Travel Cost to M-Paisa Agent (Afs) | 71.925 | 129.593 | 1691 |
| *Violence and Expectations:* | | | |
| Attack Last Month (=1) | 0.186 | 0.389 | 1699 |
| Attack This Month (=1) | 0.166 | 0.372 | 1696 |
| Expects Violence (=1) | 0.241 | 0.428 | 1446 |
| *Savings and Expenditure:* | | | |
| Cash Savings (Afs) | 6360.401 | 31659.076 | 1592 |
| Expenditure (Afs) | 26748.62 | 49799.938 | 1711 |
| Bank Savings (Afs) | 7439.492 | 84129.152 | 1629 |
| Cash Transfers (Afs) | 8374.625 | 20628.509 | 1711 |

Table 3: Treatment Effects by Violence Expectations

| Dependent Variable: | M-Paisa Balance (Afs) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | 6964.21*** | 6976.23*** | 7629.85*** | 7802.61*** | 7709.49*** | 7169.27*** |
| | (1020.94) | (1039.50) | (1081.11) | (1388.57) | (1374.56) | (1429.11) |
| Treat 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) |
| Sample | All | All | All | All | All | All |
| Mean Dep Var | 3114.97 | 3114.97 | 3114.97 | 3153.96 | 3153.96 | 3153.96 |
| # Employees | 335 | 335 | 335 | 334 | 334 | 334 |
| # Observations | 2018 | 2018 | 2018 | 1418 | 1418 | 1418 |
| R-Squared | 0.09 | 0.19 | 0.09 | 0.11 | 0.22 | 0.10 |
| 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 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. Regressions include month, 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 savings.

Table 4: Effect of Violence on Cash Savings

| Dependent Variable: | Cash Savings (Afs) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treat x Post | 3563.33 | 3511.60 | 2894.64 | | | |
| | (2534.31) | (2453.51) | (2051.37) | | | |
| Expects Violence (=1) | | | | 3744.93** | 3068.99** | 3524.88** |
| | | | | (1472.66) | (1496.42) | (1484.81) |
| Sample | All | All | All | All | All | All |
| Mean Dep Var | 4545.10 | 4545.10 | 4545.10 | 4773.16 | 4773.16 | 4773.16 |
| # Employees | 335 | 335 | 335 | 333 | 333 | 333 |
| # Observations | 1459 | 1459 | 1459 | 1244 | 1244 | 1244 |
| R-Squared | 0.01 | 0.11 | 0.02 | 0.01 | 0.10 | 0.02 |
| 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 self-reported cash holdings 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. Regressions include month, 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 savings.

Table 5: Violence and Other Economic Responses

| | (1) Cash Savings (Afs) | (2) Bank Savings (Afs) | (3) Transfers (Afs) | (4) Expenditure (Afs) |
|---|---|---|---|---|
| Expects Violence (=1) | 3384.82** | 2366.91 | 1136.51 | 1078.74 |
| | (1583.30) | (2010.71) | (1115.04) | (1575.79) |
| Sample | All | All | All | All |
| Mean Dep Var | 4497.52 | 3083.82 | 6784.73 | 23400.59 |
| # Employees | 315 | 316 | 316 | 316 |
| # Observations | 1165 | 1173 | 1233 | 1233 |
| R-Squared | 0.02 | 0.01 | 0.02 | 0.07 |
| Month FE | YES | YES | YES | YES |
| Province FE | - | - | - | - |
| Strata FE | - | - | - | - |
| Employee FE | YES | YES | YES | YES |

*Notes:* Dependent variable is self-reported cash holdings in column (1), self-reported bank deposits in column (2), self-reported transfers in column (3) and self-reported expenditures in column (4). 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. 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, bank savings, transfers and expenditures.

Table 6: Violence and Cash Savings from a Large Household Survey

| 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) |
| Sample | Trimmed | Trimmed | Trimmed | Trimmed | All |
| Mean Dep Var | 903.335 | 903.335 | 903.335 | 903.335 | 990.422 |
| # 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 INDURE 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).

# Appendices

## A Data Appendix

### A.1 Administrative Data

#### A.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.[24]

#### A.1.2 Violent incidents in Afghanistan

We integrate violence incident records covering the period January 2011 to December 2013 from the International Security Assistance Force, a multilateral military body present in since December 2001, obtained through the International Distributed Uniform Reporting Environment (INDURE). 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. These data identify two types of incidents: enemy attacks (including direct fire, indirect fire, suicide attacks and other kinetic activites) and explosions (including improvised explosive device explosions and mines strikes).

We combine both types of incidents in the empirical analysis, and attach each incident to

[24]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.

any individual with a 10 kilometer halo. That is, if an incident is further than 10 kilometer 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 an attack occurs in the 10 kilometer halo of that subscriber's location.

### A.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 labelled 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 esimate 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 $t$. In our results we use a uniform kernel such that $K(u) = 1/N_i$, however very little changes if a different kernel is specified.

# On-line Appendix: Not for Publication

## A1 Appendix Tables and Figures

Table A1: Administrative Dataset: Violence and M-Paisa Use

| Dependent Var. | M-Paisa Balance | | | Transactions (#) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Violent Event in 5 km (=1) | -144.60*** | | | -0.014*** | | |
| | (34.94) | | | (0.002) | | |
| Violent Event in 15 km (=1) | | -120.72*** | | | -0.038*** | |
| | | (37.04) | | | (0.002) | |
| Violent Event in 20 km (=1) | | | -84.84** | | | -0.045*** |
| | | | (39.48) | | | (0.002) |
| Sample | Salary Users | Salary Users | Salary Users | Salary Users | Salary Users | Salary Users |
| Mean Dep Var | 2107.34 | 2107.34 | 2107.34 | 0.191 | 0.191 | 0.191 |
| # Individuals | 7784 | 7784 | 7784 | 7784 | 7784 | 7784 |
| # Observations | 314986 | 314986 | 314986 | 314986 | 314986 | 314986 |
| R-Squared | 0.62 | 0.62 | 0.62 | 0.28 | 0.29 | 0.29 |
| Week FE | YES | YES | YES | YES | YES | YES |
| District FE | YES | YES | YES | YES | YES | YES |
| Individual FE | YES | YES | YES | YES | YES | YES |

*Notes:* Dependent variable is the M-Paisa mobile money account balance in Afghanis in columns (1)-(3), and the number of M-Paisa transactions in columns (4)-(6). Observation is an individual-week. Violence variable is a dummy for whether a violent attack was recorded in the INDURE dataset in a 5km, 15km or 20km radius of the Center of Gravity location of the M-Paisa account user as noted above. Robust standard errors, clustered at individual 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

| Dependent Var. | M-Paisa Balance | | | Transactions (#) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Violent Event in 10 km (=1) | -923.65*** | -1014.52*** | -280.15*** | 0.031*** | 0.042*** | -0.022*** |
| | (126.32) | (140.61) | (53.35) | (0.002) | (0.003) | (0.002) |
| Sample | Salary Users | Salary Users | Salary Users | Salary Users | Salary Users | Salary Users |
| Mean Dep Var | 2107.34 | 2107.34 | 2107.34 | 0.191 | 0.191 | 0.191 |
| # Individuals | 7784 | 7784 | 7784 | 7784 | 7784 | 7784 |
| # Observations | 314986 | 314986 | 314986 | 314986 | 314986 | 314986 |
| R-Squared | 0.00 | 0.01 | 0.05 | 0.00 | 0.05 | 0.08 |
| Week FE | NO | YES | YES | NO | YES | YES |
| District FE | NO | NO | YES | NO | NO | YES |
| Individual FE | NO | NO | NO | NO | NO | NO |

*Notes:* Dependent variable is the M-Paisa mobile money account balance in Afghanis in columns (1)-(3), and the number of M-Paisa transactions in columns (4)-(6). Observation is an individual-week. Violence variable is a dummy for whether a violent attack was recorded in the INDURE dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user. Robust standard errors, clustered at individual 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

| Dependent Var. | M-Paisa Balance | Transactions (#) | Withdrawals (#) | Deposits (#) | Airtime (#) | Send Money (#) |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Violent Event in 10 km (=1) | -156.51*** | -0.043*** | -0.005*** | -0.005*** | -0.011*** | -0.001*** |
| | (20.80) | (0.005) | (0.000) | (0.001) | (0.004) | (0.000) |
| Sample | All Users | All Users | All Users | All Users | All Users | All Users |
| Mean Dep Var | 1523.83 | 0.177 | 0.043 | 0.009 | 0.044 | 0.006 |
| # Individuals | 14661 | 14661 | 14661 | 14661 | 14661 | 14661 |
| # Observations | 477304 | 477304 | 477304 | 477304 | 477304 | 477304 |
| R-Squared | 0.63 | 0.26 | 0.21 | 0.21 | 0.25 | 0.13 |
| Week FE | YES | YES | YES | YES | YES | YES |
| District FE | YES | YES | YES | YES | YES | YES |
| Individual FE | YES | YES | YES | YES | YES | YES |

*Notes:* Dependent variable is the M-Paisa mobile money account balance in Afghanis in column (1), the number of M-Paisa transactions in column (2), the number of withdrawals in column (3), the number of deposits in column (4), the number of airtime purchases in column (5) and the number of peer-to-peer mobile money transfers in column (6). Observation is an individual-week. Violence variable is a dummy for whether a violent attack was recorded in the INDURE dataset in a 10km radius of the Center of Gravity location of the M-Paisa account user. Robust standard errors, clustered at individual 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: 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 A5: Treatment Effects by Violence Expectations

| | (1) | (2) | (3) |
|---|---|---|---|
| | M-Paisa Balance (Afs) | | |
| Treat x Post | 8221.40*** | 8641.70*** | 9047.30*** |
| | (2072.37) | (2268.42) | (3062.82) |
| Treat x Post x Extremely Unlikely | 1944.98 | 770.92 | -362.31 |
| | (3352.61) | (3378.89) | (4439.53) |
| Treat x Post x Not Very Likely | -2785.03 | -3616.39 | -7961.54** |
| | (2099.56) | (2676.47) | (3257.88) |
| Treat x Post x Very Likely | -3797.13* | -4092.17 | -5356.30 |
| | (2142.44) | (2550.08) | (3661.28) |
| Treat 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 A6: 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 A7: Administrative Dataset: Violence and Network Operation

| Dependent Var. | (1)<br># Towers | (2)<br># Callers | (3)<br># Calls | (4)<br># Agents | (5)<br># Agent Txns | (6)<br># M-Paisa Txns |
|---|---|---|---|---|---|---|
| Violence in District (=1) | -0.05 | -411.71 | -1116.95 | -0.01*** | -0.12 | -0.37** |
| | (0.14) | (812.55) | (3004.61) | (0.00) | (0.09) | (0.18) |
| Mean Dep Var | 6.88 | 12139.25 | 60278.50 | 0.20 | 0.86 | 3.05 |
| # Districts | 398 | 398 | 398 | 398 | 398 | 398 |
| # Observations | 29054 | 29054 | 29054 | 29054 | 29054 | 29054 |
| R-Squared | 0.03 | 0.02 | 0.03 | 0.04 | 0.01 | 0.01 |
| Week FE | YES | YES | YES | YES | YES | YES |
| District FE | YES | YES | YES | YES | YES | YES |

*Notes:* Dependent variable is the average number of active towers each day in a district in column (1), the average number of unique callers each day in a district in column (2), the average number of calls each day in a district in column (3), the average number of agents each day in a district in column (4), the average number of M-Paisa agent transactions each day in a district in column (5), and the average number of M-Paisa transations each day in a district in column (6). Observation is a district-week. Violence variable is a dummy for whether a violent attack was recorded in the INDURE dataset in a district in that week. Robust standard errors, clustered at district level, in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: Treatment Effects by Violence Expectations - Robustness

| Dependent Var. | M-Paisa Balance (Afs) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Treat x Post | 6583.31*** | 5767.57*** | 6977.71*** | 7735.32*** |
| | (1344.84) | (1027.98) | (1535.72) | (1748.58) |
| Treat x Post x Expects Violence | -4587.16** | -5328.01** | -4615.50** | -5131.05** |
| | (2264.56) | (2413.49) | (2274.12) | (2440.31) |
| Treat x Post x HH Shock | 3567.14 | | | |
| | (4852.61) | | | |
| Treat x Post x Salary Problem | | 10280.70 | | |
| | | (7050.87) | | |
| Treat x Post x Low Salary Satisfaction | | | 963.97 | |
| | | | (3972.70) | |
| Treat 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 A9: Violence and Transaction Costs

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | M-Paisa Balance (Afs) | | | | |
| Treat x Post | 7169.27*** | 7357.99*** | 6262.58*** | 7937.36*** | 8039.58*** |
| | (1429.11) | (1616.93) | (2162.46) | (1525.25) | (2196.03) |
| Treat x Post x Expects Violence | -4488.86** | | -3469.45 | | -3692.22 |
| | (2226.22) | | (3099.60) | | (3082.06) |
| Treat x Post x High Time to Agent | | -709.58 | 1510.54 | | |
| | | (2031.63) | (3068.30) | | |
| Treat x Post x Expects Violence x High Time to Agent | | | -2466.12 | | |
| | | | (4720.16) | | |
| Treat x Post x High Cost to Agent | | | | -2235.34 | -2215.53 |
| | | | | (2074.51) | (3054.75) |
| Treat x Post x Expects Violence x High Cost to Agent | | | | | -2103.61 |
| | | | | | (4387.28) |
| Sample | All | All | All | All | All |
| Mean Dep Var | 3153.96 | 2914.71 | 3178.46 | 2913.60 | 3178.84 |
| # Employees | 334 | 324 | 323 | 321 | 320 |
| # Observations | 1418 | 1670 | 1407 | 1661 | 1398 |
| R-Squared | 0.10 | 0.11 | 0.11 | 0.11 | 0.11 |
| Month FE | YES | YES | YES | YES | YES |
| Province FE | - | - | - | - | - |
| Strata FE | - | - | - | - | - |
| Employee FE | YES | YES | YES | YES | 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?" Extremely likely and very likely are coded as Expects Violence. High Time to Agent represents above the median in reported travel time to the nearest M-Paisa agent. High Cost to Agent represents above the median in reported travel cost to the nearest M-Paisa agent. 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 A10: M-Paisa Balance - Violence Expectations and Violence Exposure

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | M-Paisa Balance (Afs) | | | |
| Treat x Post | 13169.65*** | 7169.27*** | 10985.53*** | 12232.55*** |
| | (2528.21) | (1429.11) | (2443.62) | (2745.10) |
| Treat x Post x Attacks | -196.61*** | | -141.52** | -187.29*** |
| | (63.91) | | (54.65) | (67.38) |
| Treat x Post x Expects Violence | | -4488.86** | -3995.67* | -8958.74*** |
| | | (2226.22) | (2169.40) | (3345.89) |
| Treat x Post x Expects Violence x Attacks | | | | 179.03** |
| | | | | (70.04) |
| Attacks | 50.78*** | | 11.01 | 45.00** |
| | (15.91) | | (21.92) | (22.74) |
| Expects Violence (=1) | | 470.46 | -251.19 | 1930.06** |
| | | (395.99) | (826.23) | (814.76) |
| Sample | All | All | All | All |
| Mean Dep Var | 3114.97 | 3153.96 | 3153.96 | 3153.96 |
| # Employees | 335 | 334 | 334 | 334 |
| # Observations | 2018 | 1418 | 1418 | 1418 |
| R-Squared | 0.10 | 0.10 | 0.11 | 0.11 |
| Month FE | YES | YES | YES | YES |
| Strata FE | - | - | - | - |
| Employee FE | YES | YES | YES | 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 Attacks variable measures the number of insurgent-related attacks in a provincial district capital over the month as recorded in the INDURE dataset (see paper text for 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. 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. Trimming top .5% of outliers in cash savings.

Table A11: Violence and Cash Savings from a Large Household Survey

| 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.