Flexible Microfinance Products to Cope with Shocks: Evidence from SafeSave

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Abstract

Shocks are usual in the poor lives. Evidence shows that the poor barely edge against shocks. This paper provides an analysis of the extend to which households use flexible microfinance products to cope with shocks. We examine a unique dataset released by SafeSave, a microfinance institution serving poor slum dwellers in Dhaka, Bangladesh. Using SafeSave administrative data on daily transactions and balances of more than 10,000 accounts over seven years, we find that saving and borrowing respond to both expected and unexpected shocks. Namely, we find that cash-ins, i.e. savings deposits and loan repayments, into SafeSave accounts are concentrated on the days following wage payments. In addition, savings balances drop, and outstanding loan balances raise during Muslim festivals. Finally, saving and borrowing respond to the general shutdown of activities during nationwide political strikes (*hartals*).

Keywords: microfinance, consumption smoothing, liquidity, Bangladesh.

JEL codes:

1. Introduction

The lives of the poor are marked not only by low income, but also by highly variable income streams and expenditure shocks. At low income levels, mechanisms to cope with economic shocks are particularly important since shocks can have devastating effects and lead resources to fall below what is required to cover basic needs (Townsend, 1995; Morduch, 1995). Unfortunately, the poor barely hedge against shocks (Collins *et al.*, 2009). They have limited formal insurance. Being dependent on the social network for insurance can be psychologically and practically costly (Baland *et al.*, 2011) and it proves to be inefficient under common shocks (Townsend, 1994).

Can well-designed microfinance (microcredit and micro-savings) products address this market failure? This paper provides an analysis of the extend to which households use *flexible* microfinance products to cope with shocks. We explore this issue using a unique data set released by SafeSave, a microfinance institution offering flexible savings-and-loan accounts to the poor living in Dhaka slums. Our analysis shows that the response of saving and borrowing to economic shocks is large and statistically significant.

Savings and borrowing are meant for consumption smoothing. The celebrated life-cycle and permanent income models (henceforth, LC theory)—due to Modigliani and Brumberg (1954) and Friedman (1956)—posit that people use saving and borrowing to smooth income fluctuation. Among the rich, the LC theory is well documented (Jappelli & Pistaferri, 2010).

Among the poor—precisely in microfinance—the LC theory is controversial. Why? Generally, the poor are more saving and credit constrained than rich (ref); hence, the poor may not have the proper financial (savings and credit) products to cope with shocks. In the specific case of microfinance, microcredit and micro-savings products are rigid and standardized, and consequently cannot be used as insurance for emergencies, or for income and expenditure shocks (Labie *et al.*, 2015). Typical microcredit reimbursement and repayment follow a rigid schedule: short-term duration, small and frequent installment starting after loan disbursement, progressive lending and zero tolerance toward default (Armendariz & Morduch, 2010). Also savings are compulsory; they follow the same rigid structure of loans, serving as financial collateral. Over the years, rigid microcredit features have proven to stimulate clients' repayment conduct. However, they have also resulted in lack of flexibility.[1]

From a theoretical standpoint, flexible microcredit and micro-savings products are especially well suited to cope with shocks. According to Collins *et al.* (2009), financial product flexibility "refers to the ease with which transactions can be reconciled with cash-flows" (p. 181). Flexible features include: grace periods in loan reimbursements, fee-free rescheduling options in case of shock, credit lines, liquid savings accounts with discretionary deposits and withdrawals, etc. In addition, financial flexibility is also a way to understand what people really want.

The main objective of this paper is to examine whether and how saving and borrowing in flexible microfinance products respond to income shocks (i.e. events that determine an income fluctuation). We exploit a unique database released by SafeSave, a microfinance institution offering flexible savings-and-loan accounts to the poor living in the slums of Dhaka, Bangladesh. SafeSave savings-and-loan accounts are probably the most salient example of flexible microfinance product: deposits and withdrawals can be made at any time for any amount; loans are repaid freely with no maturity or fixed installments (Laureti & Hamp, 2011).

Our dataset consists of daily financial movements by 10,631 SafeSave clients in their savings-and-loan accounts for the period stretching from January 2004 to August 2012. We classify SafeSave clients into two groups. Borrowers (77%) have taken at least one loan from SafeSave during the observation period. Non-borrowers (23%) have never borrowed from SafeSave; they use their account only for saving. Importantly non-borrowers have the possibility to borrow but choose spontaneously not to do so. SafeSave clients belong to four different slum areas, namely Gonoktuli, Kurmitola, Millat and Muslim. We aggregate data at the slum level, and examine average per-client (or aggregate) saving and borrowing over time.

[1] Concerns have increasingly been voiced about perverse effects of rigidity in microcredit products, such as reduced financial access and over-indebtedness (Guirkinger, 2008; Guerin et al., 2011; Pearlman, 2012; Mallick, 2012; and Schicks, 2013).

The paper examines Safesave clients' response to common (income) shocks. We examine both expected and unexpected shocks. Among the expected shocks, we look at paydays and Islamic festivals.[2] During paydays, workers face an anticipated increase of income. By contrast, during Islamic festivals, individuals face an anticipated income decline (and/or an anticipated expenditure increase). For example, during *Ramadan*, adult Muslims are required to fast from dawn to sunset for 30 days. Schofield (2014) demonstrates that fasting during *Ramadan* decreases the productivity of rickshaw workers in India.

To detect the response of SafeSave clients to expected shocks, we run OLS regressions that include, among the regressors, time fixed effects. We use both Gregorian calendar and Islamic calendar fixed effects. Times fixed effects allow us to identify seasonality in aggregate saving and borrowing. This analysis shows that SafeSave clients use their accounts in response to paydays and Islamic festivals. First, our data show that cash-ins, i.e. savings deposits and loan repayments, into SafeSave accounts are concentrated on the days following wage payments. For irregular workers, who perceive a weekly wage on Thursdays (i.e. end of working week), cash-ins are the highest on Saturdays (i.e. beginning of new working week). For regular workers, who perceive a monthly wage on the first week of the Gregorian months, cash-ins are the highest on the second week of the Gregorian months. Second, savings balances drop (and outstanding loan balances rise) tremendously during *Ramadan*, occurring between week 45th and 49th of the Islamic calendar. Finally, we find significant reaction of SafeSave clients to other two Islamic festivals: *Id al-Fitr* (i.e. the end of *Ramadan*) and *Id al-Adha* (i.e. the feast of sacrifice).

Among the unexpected shocks, we investigate the response of SafeSave clients to nationwide political strikes (called "*hartals*"). The literature shows that *hartals* determine an income loss, especially in occasion of the most severe *hartal* events, including two or more consecutive *hartal* days (ActionAid Bangladesh, 2000; UNDP, 2005; Roy & Hossain, 2013; Ashraf *et al.*, 2015). *Hartal* events are announced, on average, 5.5 days in advance (Roy & Hossain, 2013). Hence, we consider

[2] 90% of Bangladeshis are Muslim.

hartal as a unexpected shock because the intensity (i.e. duration) of the *hartal* event is unknown in advance. To detect SafeSave clients' response to *hartals*, we examine the residual components of saving and borrowing, obtained by removing trend and seasonality from the original time series.

Our main finding is that SafeSave clients respond to *hartal* events…... [To be continued, see p. 13 for description of results and pp. 32-35 for the Tables on hartal regressions]

The microfinance literature has little evidence on the advantages and disadvantages of flexible products in general,[3] and if they are useful to cope with shocks in particular. Empirical studies (Shoji, 2010; Shonchoy and Kurosaki, 2014; Kast and Pomeranz, 2014; Prina, 2015) examine the impact of product flexibility on consumption smoothing and evidence is mixed. Shoji (2010) shows that loan rescheduling after the 2004 nation-wide flood in Bangladesh reduced the likelihood that victims skip a meal. In contrast, observing farmers from Northwest Bangladesh who were given temporary moratorium during the lean season ("monga") that follows the transplantation of the Aman rice crop, Shonchoy and Kurosaki (2014) provide evidence that repayment flexibility does not affect consumption levels. Two RCTs—Kast and Pomeranz (2014) in Chile; and Prina (2015) in Nepal—show that access to a fully liquid savings account can help individuals improve consumption smoothing in the face of income shocks.

This paper contributes to the above literature in at least two ways. First, previous literature has shown the benefits for consumption smoothing of liquid savings accounts (Kast & Pomeranz, 2014; Prina, 2015) and of *ex-post* loan rescheduling in microcredit contracts (Shoji, 2010). We provide the first evidence on the risk-coping benefits of fully flexible microcredit contracts. Second, previous literature examines the effect of shocks on (subjective) consumption data. In contrast, we look at the effect of shocks on individual saving and borrowing. The advantage is that our data are not affected

[3] For an overview on flexible microfinance products, see Labie *et al.* (2015).

by individual subjective perception. The limit is that we cannot test whether product flexibility improve consumption smoothing (Udry, 1995).[4]

The remainder of the paper is organized as follow. Section 2 presents the dataset. Section 3 examines the use of SafeSave accounts to cope with expected shocks. Section 4 examines the use of SafeSave accounts for unexpected shocks. Section 5 concludes.

2. Data

This paper examines how the poor use flexible microfinance products to cope with expected and unexpected shocks. We use a unique database released by SafeSave, a financial co-operative offering micro-savings and microcredit products to the poor and very poor people living in the slums of Dhaka (Bangladesh). As of June 2012, SafeSave had nine branches serving 17,540 clients. Its savings balance amounted to BDT 75 million, with an average savings balance per client of BDT 4,152 (equivalent to approximately USD 52). About half of SafeSave's clients hold loans, worth a total of BDT 45 million, with an average outstanding balance of BDT 5,038 (USD 63) per borrower. SafeSave is one of the few MFIs worldwide that offers flexible microfinance products (Dehejia *et al.*, 2012).

We observe movements on SafeSave's flexible savings-and-loan accounts. These are fully liquid no-maturity accounts. Deposits and withdrawals can be made at any time for any amount. Deposit collectors visit each client daily. This practice encourages deposits and also makes savings immediately accessible. SafeSave's active clients—16 years old and up—are also allowed to borrow. The maximum loan amount increases with good repayment history; importantly it can never exceed three times the outstanding savings balance. Clients can access a new loan only after the previous one is fully repaid. Moreover, SafeSave allows only one loan per household. Loans are repaid freely, with no maturity or fixed installments. The only compulsory payments are the monthly interests. At

[4] Udry (1995) also look at households' assets data to test the use of saving behavior to smooth income fluctuations over time.

August 2012, clients pay a 30% yearly interest on outstanding debt and earn a 6% yearly interest on savings balance.

The unbalanced panel dataset is made of 12,648,625 day-client observations, relative to 10,631 clients for the period from January 2004 to August 2012. We focus on four SafeSave branches (i.e. Gonoktuli, Kurmitola, Millat and Muslim). From the original dataset made of 16,071 clients, we selected the 12,244 *potential* borrowers, i.e. SafeSave clients who are allowed to borrow. Finally, we trim the data by ignoring the 1,613 individuals with extreme value of transactions and/or balances (precisely, we exclude clients with the 5% highest transactions—i.e. savings deposits, withdrawals, loan repayments, and loans—and with the 5% highest savings balances and outstanding loan balances).

Table 1 provides summary statistics of variables of interests. The global sample of potential borrowers (N=10,631) is classified into borrowers and non-borrowers. Borrowers (77%) are SafeSave clients' who have taken at least one loan during the study period. In contrast, non-borrowers (23%) have never borrowed during the study period; importantly, non-borrowers are allowed to borrow, i.e. they are more than 16 years old and belong to non-borrowing households.

The majority of individuals are women (85%). The average individual in the sample is in her thirties and has been holding a SafeSave account for two years. In total, 45% of individuals declare no professional occupation. Among those with an occupation, the majority (78%) have irregular jobs. "Irregular" workers include self-employed, who earn their income on a daily/weekly basis and often of irregular amounts. Self-employed are: transport laborers (e.g. rickshaw drivers), ship-owners and shopkeepers, unskilled daily laborers (e.g. construction workers or brick breakers), handicraft workers, street traders, and other small business owners. In contrast, 22% have regular jobs in the formal sector. "Regular" workers have a job in the formal sector. They earn a regular, fixed wage, typically paid on a monthly basis. The vast majority (72%) of the formal sector is made of workers in garment factories. The rest are guards at schools or hotels, teachers, medical staff of hospital, or home servants. “No occupation” includes mostly housewives (95%); the rest are students (4%), unemployed, and retired people. (See table A1 in the appendix for details of types of occupations).

In our sample, average savings balance among non-borrowers is BDT 605 BDT (USD 8).[5] Average savings balance among borrowers is BDT 1,448 (USD 18) and the average outstanding loan is BDT 2,624 (USD 33). Taking into account that clients should hold compulsory savings equal to one-third of the outstanding loan, liquid savings, i.e. savings exceeding the compulsory amount, are BDT 574 (USD 7).

Dynamics over time of average per-client savings balances and outstanding loan balances is represented in Figs. 1 and 2, for non-borrowers and borrowers respectively. For this analysis, we focus on the period starting from January 2006. In fact, on January 2006 all four branches are mature and growth rates of savings balances and outstanding loan balances are constant.[6] Figs. 1 and 2 depict a huge savings accumulation both among non-borrowers and borrowers. Average per-client liquid savings balances among non-borrowers and borrowers grow at 18% and 16% rate per year, respectively. Among borrowers, average per-client outstanding loan balances grow at 6% per year. Average inflation rate in the same period is 7.9% (http://data.worldbank.org).

The augmented Dickey-Fuller test for unit root, a typical test to check stationarity of time series, shows that the time series of transactions—i.e. savings deposits, withdrawals into savings, loan repayments and loans taken—are stationary, but savings balances and outstanding loan balances are not. Non-stationarity can be due to the presence of trend and seasonal components. We isolate trend and seasonal components of savings and borrowing in the next session.

[5] 1 US dollar (USD) is equivalent to about 80 Bangladeshi takas (BDT).
[6] Starting dates of the four branches are: 5-Jan 2004 Millat; 15-Mar 2005 Muslim; 8-Sep 2005 Gonoktuli; and 1-Nov 2005 Kurmitola.

3. Expected Shocks: Paydays and Islamic Festivals

In this section, we investigate whether SafeSave clients use flexible savings-and-loan accounts to cope with expected shocks (that is, an event that determines an expected variation of income and/or expenditure). We focus on two common shocks: paydays and Islamic festivals.

Both paydays and festivals occur regularly. While paydays are linked to the Gregorian calendar, festivals occurrence follows the Islamic (or lunar) calendar. Therefore, we run the following ordinary least squares (OLS) regression at the branch level:

$$Y_{bt} = \beta_{t^g} + \gamma_{t^i} + \alpha_b + T_{bt} + Y_{b,t-1} + \eta_{bt} \quad (1)$$

where Y_{bt} is an (aggregate) outcome variable for branch b at time (day) t. Outcome variables are average per-client: savings balances, outstanding loan balances, savings deposits, withdrawals from savings, loans taken, and loan repayments. The terms β_{t^g} and γ_{t^i} represent time fixed effects: β_{t^g} represents time fixed effects according to the Gregorian calendar; and γ_{t^i} controls for time fixed effects according to the Islamic calendar. The term α_b controls for branch fixed-effects; T_{bt} is a quadratic trend and $Y_{b,t-1}$ is the lagged dependent variable. Finally η_{bt} is the error term.

We estimated Eq. (1) for the group of borrowers and the group of non-borrowers separately, and including the observation period from January 2006 to August 2012. Figs. 3 to 8 represent time fixed-effects computed from Eq. (1). The coefficients estimates of the OLS regression in Eq. (1) are shown in Tables 2 and 3, for non-borrowers and borrowers respectively.

Figs. 3 and 4 represent the days-of-week fixed effects among non-borrowers and borrowers respectively. Figs. 3bis and 4bis plot the day-of-week fixed effects by occupational category. Cash-ins (i.e. savings deposits and loan repayments) into SafeSave accounts are the highest on Saturdays and decrease throughout the Islamic week; on Thursdays, the final working day of the week, cash-ins reach their lowest value. Irregular workers drive this effect. In fact, irregular workers are paid weekly, at the end of the week, on Thursdays; since SafeSave is closed on Fridays, clients save (down or up) on Saturdays. Fig. 4 also shows that on Saturdays loans taken are relatively low, and withdrawals are relatively high. This dynamic is explained by the fact that SafeSave discourage its clients to take loans on Saturdays.

Figs. 5 and 6 depict week-of-Gregorian-month fixed effects among non-borrowers and borrowers respectively. Figs. 5bis and 6bis plot the week-of-Gregorian-month fixed effects by occupational category. We observe a concentration of cash-ins in the second week of each Gregorian month. Regular workers drive this effect. According to Bangladeshi law, garment factory workers—that represent the great majority of regular workers in our sample—should be paid on the first week of the following month.[7] Coherently, we observe a concentration of cash-ins in the second week of each Gregorian month. Our regression results show that individuals make savings deposits and loan repayments during paydays. In other words, individuals save (up and down) (Rutherford, 2000) when their income is high. We also observe the highest concentration of loans taken in the second week of each Gregorian month (Graph D of Fig. 6). This dynamic occurs as SafeSave clients can take new loans only when they finish to repay the previous one.

Figs. 7 and 8 illustrate Islamic week fixed effects for non-borrowers and borrowers, respectively. Fig. 7 shows savings balances decrease during *Ramadan* and *Id al-Fitr,* that is the end of *Ramadan* (approximately weeks 35 to 39). A similar dynamics of liquid savings is observed among the group of borrowers (Graph A of Fig. 8). In addition, outstanding loan balances among borrowers increase sharply in the period around *Ramadan* and *Id al-Fitr* (Graph B of Fig. 8).

Figs. 7 and 8 show that savings balances decrease and outstanding loan balances increase during another Islamic festival: *Id al-Adha*, the Feast of Sacrifice occurring at weeks 48 and 49.

As shown in Tables 2 and 3, we include the lagged variable $Y_{b,t-1}$ for savings balances and outstanding loan balances. In fact, behavioral response should be in flows, not in stock. Deposits, withdrawals are flows. Balances are not. What we really want are the net of deposits and withdrawals, which is the change in savings balances. Alternatively we could have used "change in

[7] http://www.globallabourrights.org/reports/document/0403-IGLHR-DisneySweatshopInBangladeshNiagra.pdf, retrieved on 13th May 2016.

savings balances” and “change in loan balances”. As the coefficients on the lagged variable are close to one, this will give the same results.

Finally, the problem of non-stationarity of savings balances and outstanding loan balances is solved thanks to the quadratic trend[8] and the lagged dependent variable (in fact, the augmented Dickey-Fuller test for unit root gives that residuals of Eq. (1) are stationary).

4. Unexpected Shocks: *Hartals*

In this section we investigate the use of SafeSave accounts to cope with nationwide political strikes (*hartals*).

Hartals are common in Bangladesh and typically intensify as the country approaches political elections. Studies (e.g. ActionAid Bangladesh, 2000; UNDP, 2005; Roy & Hossain, 2013; Ashraf *et al.*, 2015) show that *hartals* have relevant economic costs, such as absence of work for daily earners during *hartals*, disruptions in transport system leading to shortage in food supply, and increasing prices; default loans due to a slump in business activities.

The data on *hartal* are not readily available. We collected information on *hartal* from the Daily Star, the most popular English language daily newspaper in Bangladesh. A *hartal* event can be as short as 6 hours or it may last for multiple days. Henceforth, we distinguish *hartal* events and *hartal* days. A *hartal* event is “severe” if it lasts for minimum two consecutive days. In the period from 2006 to 2013, we count 36 *hartal* days:[9] 20 days (60%) are isolated; the remaining 16 *hartal* days belong to five severe *hartal* events.

We expect a *hartal* day to affect savings and borrowing: on the same day (simultaneous effect), on the days preceding the *hartal* day (anticipation effects) and on the days following the *hartal* day (recovery effect) (Roy & Hossain, 2013; Ashraf *et al.*, 2015). In our sample period, *hartal* events are

[8] We also use log-linear trend, and results are robust.
[9] The hartal of January 1, 2006, is excluded from the analysis. In fact on the same day SafeSave pays the interests on savings directly into the savings accounts, generating a huge increase of savings balances, especially among borrowers (see graphs in the appendix). As we use dummy variables to control for the days when SafeSave pays interests, the hartal effect occurring on interest-payment days cannot be detected.

announced, on average, 5.5 days in advance (Ahsan and Iqbal, 2014, p. 24). However, while a *hartal* event may be expected, the length (intensity) of the *hartal* events is unexpected.

To examine the response of saving and borrowing *to hartals,* we run the following OLS regression at the branch level:

$$\eta_{bt} = \theta_1 H1_{bt} + \theta_2 H2_{bt} + \sum_m \varphi_m H_{b,t-m} + \omega_{wt} \qquad (2)$$

where η_{bt} is the residual of Eq. (1) in branch b at time (day) t. Outcomes variables are (the residuals of) the average per-clients: deposits into savings, withdrawals from savings, loan repayments and loans taken. The regressors include a series of *"hartal*" dummies indicators. Precisely, $H1_{bt}$ takes value 1 for the first day of *hartal* (i.e., all isolated *hartals* and the first day of a severe *hartal*) and 0 otherwise; $H2_{bt}$ takes value 1 for the second and third consecutive *hartal* days, and 0 otherwise. $H_{b,t+m}$ is an indicator variable for the (no-*hartal*) days before and after the *hartal*, where $m = -5, -4, -3 - 2, -1,\ 1,\ 2,\ 3,\ 4,\ 5$. [10] Finally, ω_{wt} is the error term.

We estimate Eq. (2) in the period from January 2006 to August 2012. Regression results are displayed in Table 4 for non-borrowers, and Tables 5 and 6 for borrowers. (In Tables 4bis, 5bis and 6bis we run regression in Eq. (2) in the estimation period including the 10 days before and the 10 days after the *hartal* events. Results are robust.)

Tables 4 and 4bis for non-borrowers:

- Savings deposits are lower on the two days before the hartal event, during the *hartal*, and on the first day after the hartal;
- Withdrawals are significantly lower 2 days before the *hartal*.

[10] We estimate Eq. (2) using different lags and leads, and results are robust.

- Net savings (=deposits – withdrawals) decrease starting two days before the *hartal* event until the end of the *hartal*. They increase as soon as the hartal finish (see figure D1 in the Appendix, p. 45).

Tables 5 and 5bis for borrowers (saving behavior):

- Savings deposits are lower on the day before the hartal event, during the *hartal*, and on the first day after the hartal
- Withdrawals are significantly lower 4 days before the *hartal*.
- Net savings (=deposits – withdrawals) increase until the first day of *hartal*; it decreases on the second and third hartal days (see figure D2 in the Appendix, p. 46).

Tables 6 and 6bis for borrowers (borrowing behavior):

- Loan repayments are significantly lower on the two days before the *hartal*
- Loans taken are significantly lower on the days before the *hartal* and on the first day of *hartal*
- Net borrowing (loans taken minus repayments) decrease until the first day of hartal; it increase on the second and third hartal days (see figure D3 in the Appendix, p. 47).

5. Conclusion [to do]

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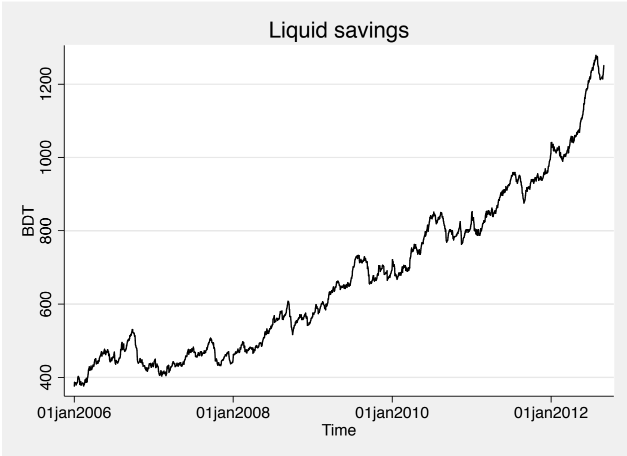
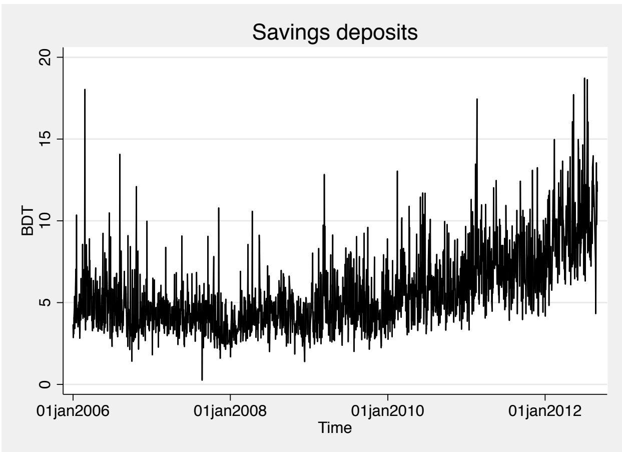
Figures and Tables

Figure 1
Average per-client savings balances, deposits and withdrawals among non-borrowers

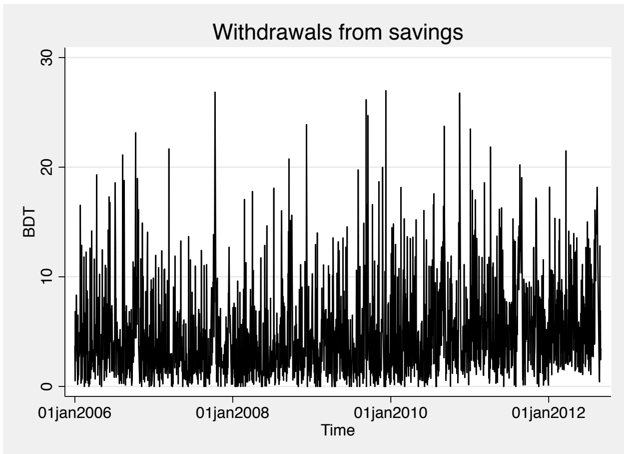
Graph A



Graph B



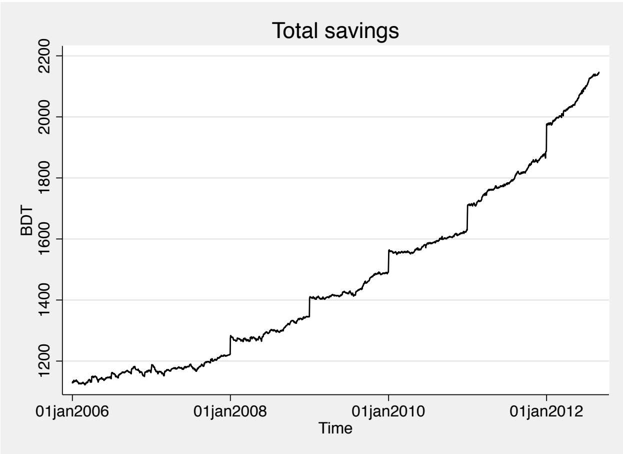
Graph C



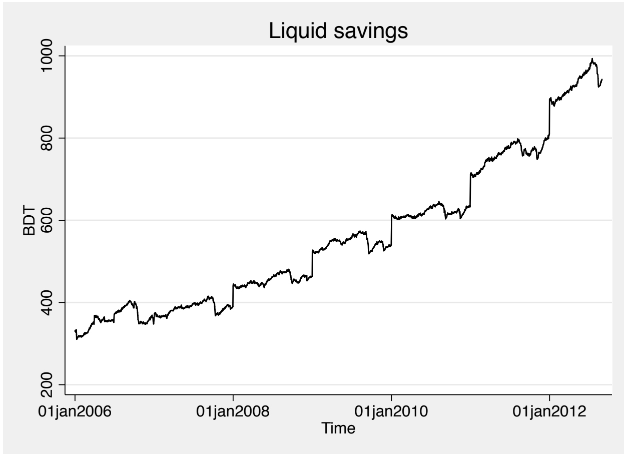
Notes: Fig. 1 displays the dynamics of the average per-client liquid savings balances (graph A), savings deposits (graph B) and withdrawals from savings (graph C) in the period from January 2006 to August 2012 among non-borrowers. Non-borrowers do not borrow and do not have any compulsory savings requirement. Hence, the entire amount of their savings is liquid. We check stationarity (augmented Dickey-Fuller test for unit root). Withdrawals and deposits are stationary. Liquid savings balances are non-stationary. All the time series are serially correlated (Portmanteau test for white noise).

Figure 2a
Average per-client savings balances, deposits and withdrawals among borrowers

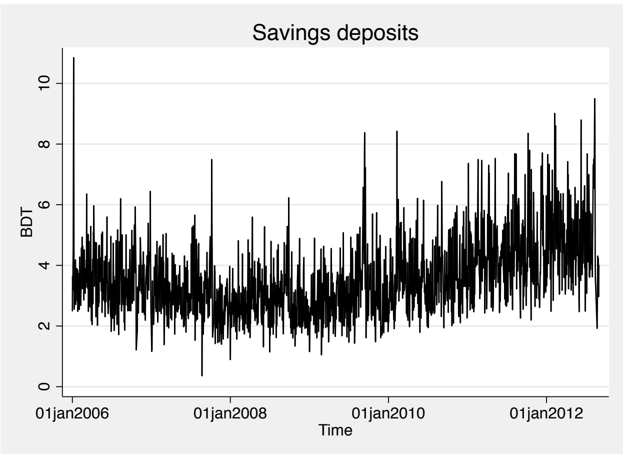
Graph A



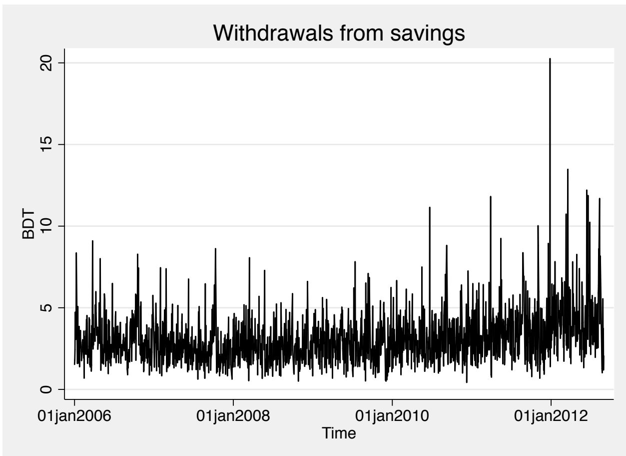
Graph B



Graph C



Graph D

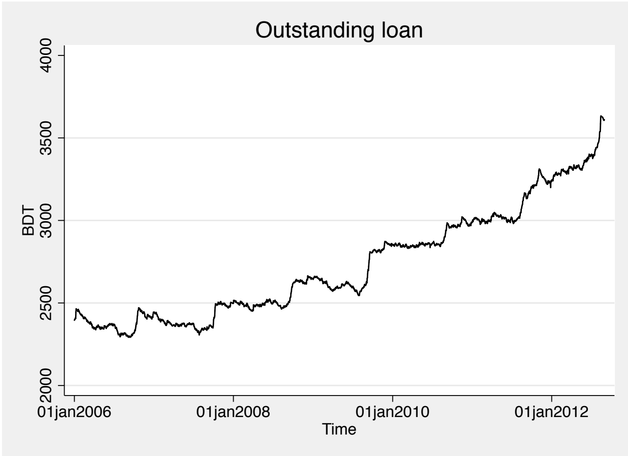


Notes: Fig. 2a displays the dynamics of the average per-client total savings balances (graph A), liquid savings balances (graph B), savings deposits (graph C) and withdrawals from savings (graph D) in the period from January 2006 to August 2012 among borrowers. SafeSave obliges borrowers to keep compulsory savings equal to 0.33 of the outstanding loan balance. The remaining part of the savings is liquid savings, which can be withdrawn at any time. We check stationarity (augmented Dickey-Fuller test for unit root). Financial transaction time series (i.e. withdrawals and deposits) are stationary. (Total and liquid) savings balances are non-stationary. All the time series are serially correlated (Portmanteau test for white noise).

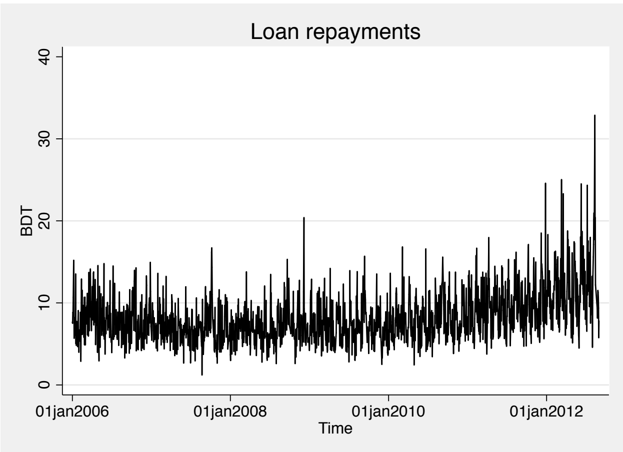
Figure 2b

Average per-client outstanding loan balances,
loan repayments and loans taken among borrowers

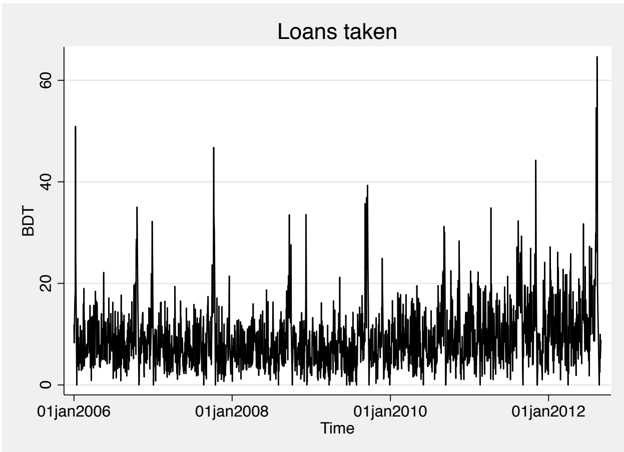
Graph A



Graph B



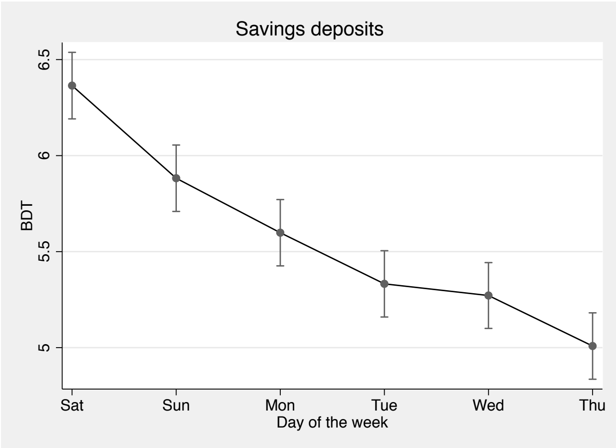
Graph C



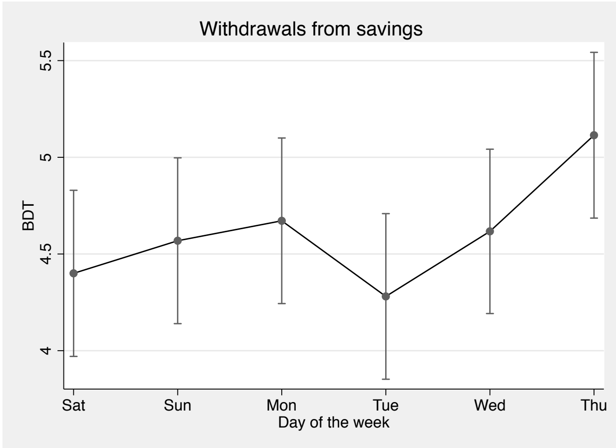
Notes: Fig. 2b displays the dynamics of the average per-client outstanding loan balance (graph A), loan repayments (graph B) and loans taken (graph C) in the period from January 2006 to August 2012 among borrowers. We check stationarity (augmented Dickey-Fuller test for unit root). Loan repayment and loans taken are stationary. Outstanding loan balances is non-stationary. All the time series are serially correlated (Portmanteau test for white noise).

Figure 3
Day of week fixed-effects among non-borrowers

Graph A



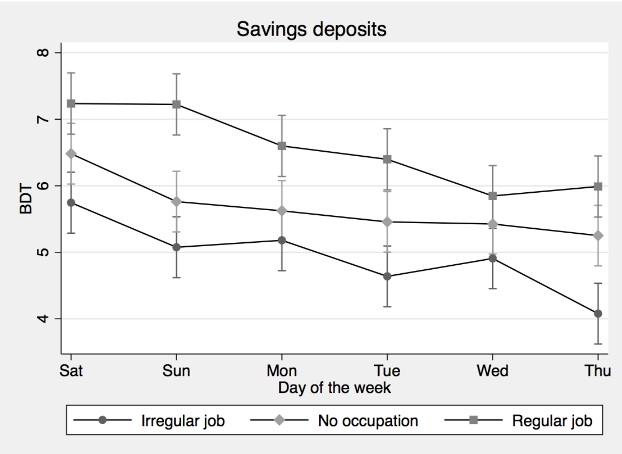
Graph B



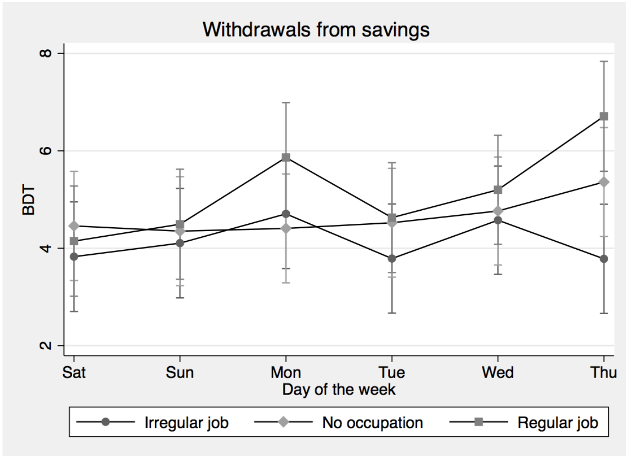
Notes: In Fig. 3, the graphs represent the day of week fixed-effects among non-borrowers. The *y*-axis reports the average per-client daily deposits (Graph A) and daily withdrawals (Graph B). We exclude Fridays from the graph because SafeSave is closed and hence transactions are null. Deposits decrease throughout the week. Withdrawals are rather constant during the days of the week.

Figure 3bis
Day of week fixed-effects among non-borrowers, by occupational category

Graph A



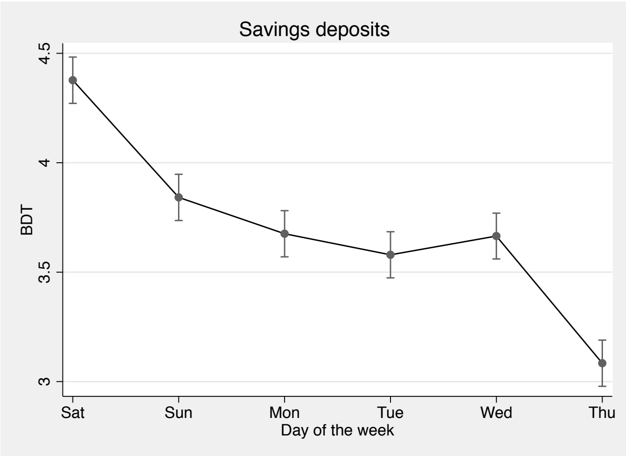
Graph B



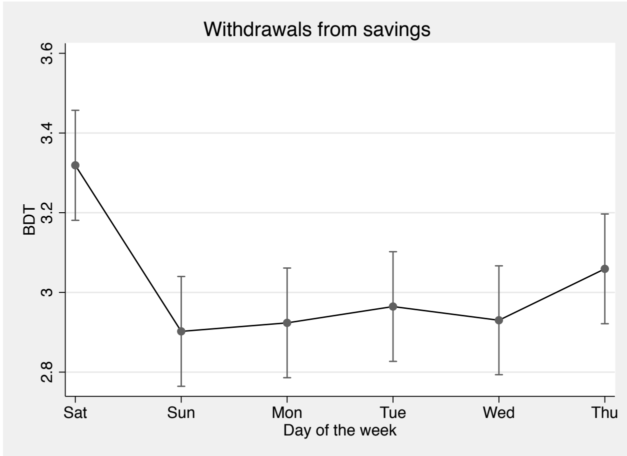
Notes: In Fig. 3bis, the graphs represent the day of week fixed-effects among non-borrowers, by occupational category. The *y*-axis reports the average per-client daily deposits (Graph A) and daily withdrawals (Graph B). We exclude Fridays from the graph because SafeSave is closed and hence transactions are null. Deposits decrease throughout the week. Irregular workers drive this dynamic: they are paid at the end of the working week (Thursdays) and make savings deposits on Saturdays.

Figure 4
Days of week fixed-effects among borrowers

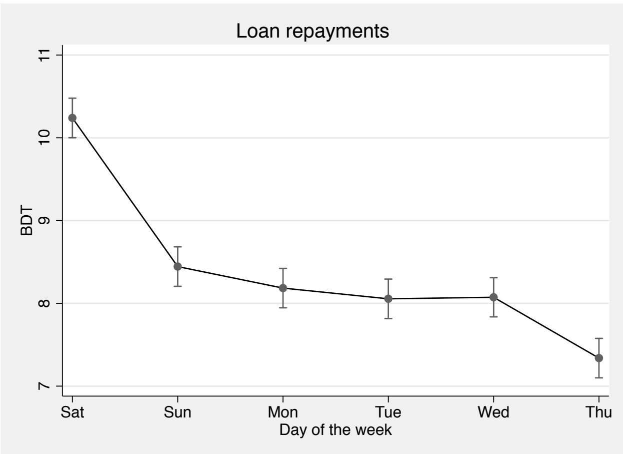
Graph A



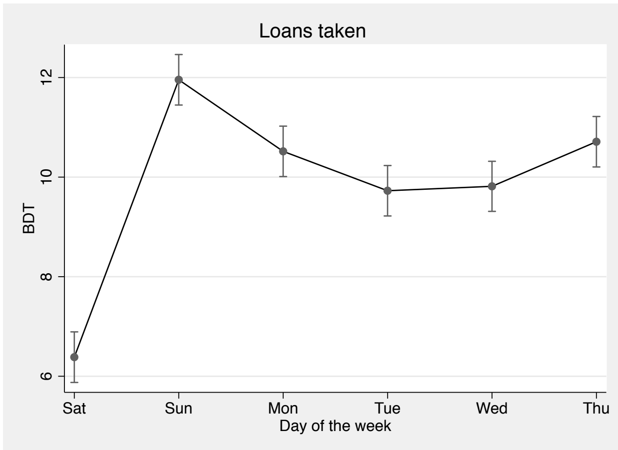
Graph B



Graph C



Graph D

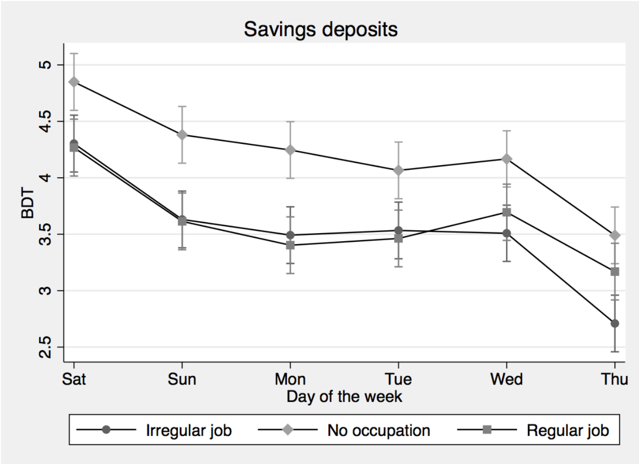


Notes: In Fig. 4, the graphs represent the day of week fixed-effects among borrowers. The *y*-axis reports the average per-client daily deposits (Graph A), daily withdrawals (Graph B), daily loan repayments (Graph C) and daily loans taken (Graph D). We exclude Fridays from the graph because SafeSave is closed and hence transactions are null. Deposits and loan repayments (Graphs A and C) decrease throughout the week. Withdrawals (and loans taken) are rather constant during the week, except for Saturday where withdrawals (loans taken) are relatively high (low).

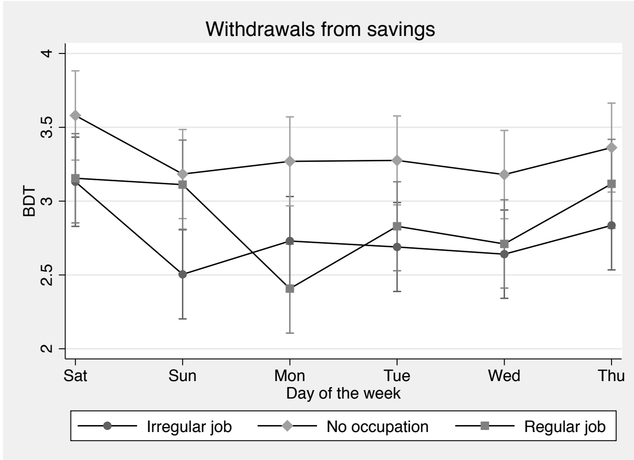
Figure 4bis

Days of week fixed-effects among borrowers, by occupational category

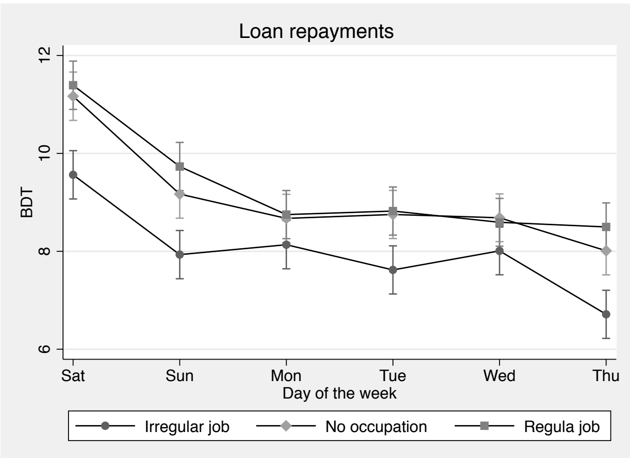
Graph A



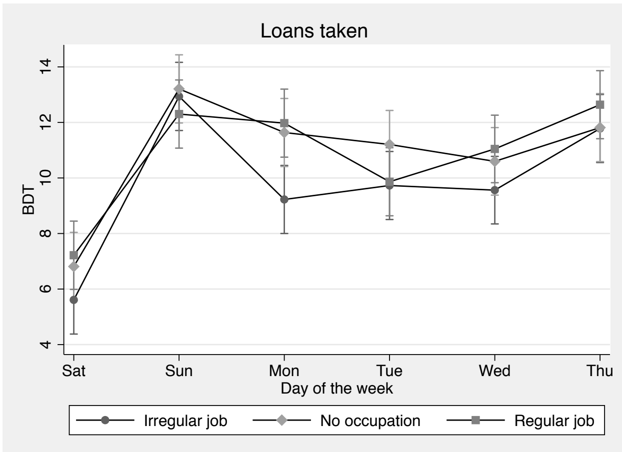
Graph B



Graph C



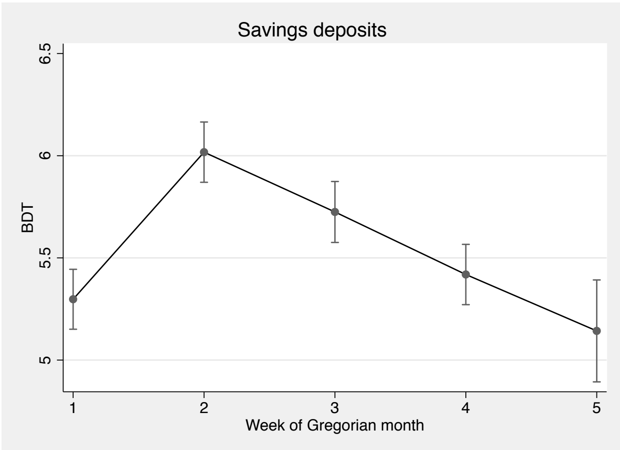
Graph D



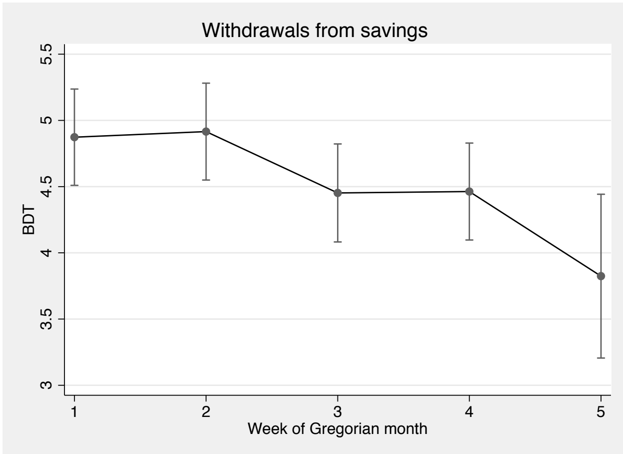
Notes: In Fig. 4bis, the graphs represent the day of week fixed-effects among borrowers, by occupational category. The *y*-axis reports the average per-client daily deposits (Graph A), daily withdrawals (Graph B), daily loan repayments (Graph C) and daily loans taken (Graph D) in logarithm. We exclude Fridays from the graph because SafeSave is closed and hence transactions are null. Deposits and loan repayments decrease throughout the week. These dynamics catch weekly payments regularities: some (regular) workers receive a weekly wage which is paid at the end of the working week (Thursdays); on Saturdays, clients use part of their income to make payments—savings deposits and loan repayments—into their accounts.

Figure 5
Gregorian week fixed-effects among non-borrowers

Graph A



Graph B

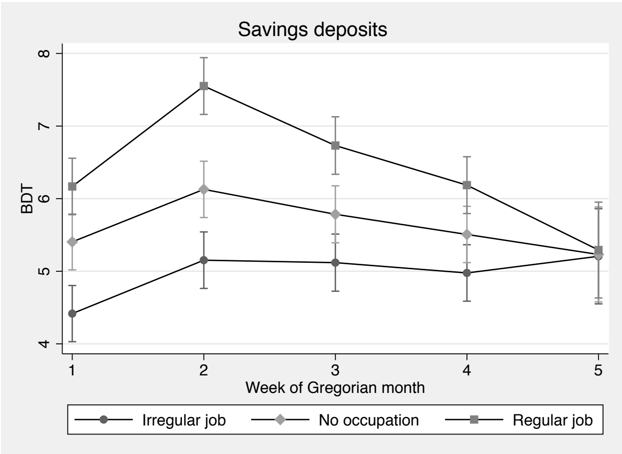


Notes: In Fig. 5, the graphs represent the Gregorian week fixed-effects among non-borrowers. The *y*-axis reports the average per-client daily deposits (Graph A) and daily withdrawals (Graph B). The *x*-axis reports the 1st, 2nd, 3rd, 4th and 5th week of Gregorian months. Weeks are defined as: 1st week includes days from 1 to 7; 2nd week includes days from 8 to 14; 3rd week includes days from 15 to 21, 4th week is days from 22 to 28; and 5th week is days from 29 to 31. According to Graph A, non-borrowers make most of their deposits the second week of each Gregorian month. In contrast, withdrawals are fairly constant during the first four weeks of the month, and they decrease toward the end of the months.

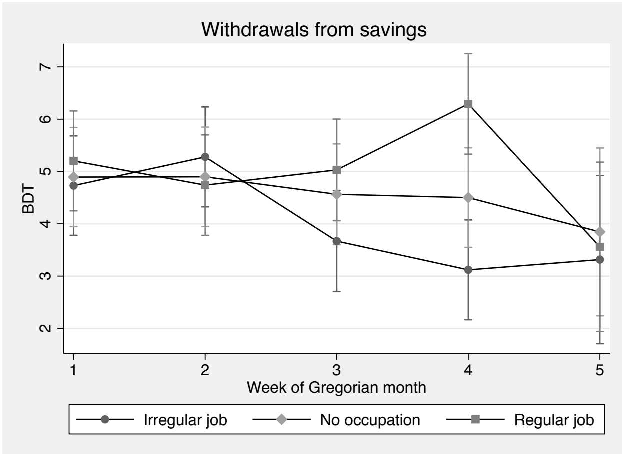
Figure 5bis

Gregorian week fixed-effects among non-borrowers, by occupational category

Graph A



Graph B

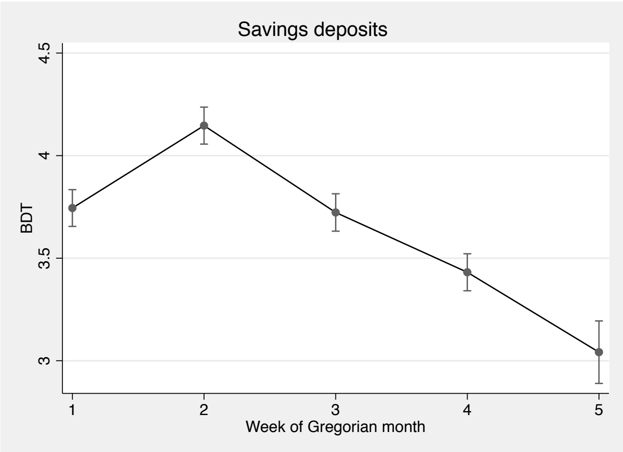


Notes: In Fig. 5bis, the graphs represent the Gregorian week fixed-effects among non-borrowers, by occupational category. The *y*-axis reports the average per-client daily deposits (Graph A) and daily withdrawals (Graph B) in logarithm. The *x*-axis reports the 1st, 2nd, 3rd, and 4th week of Gregorian months. Weeks are defined as: 1st week includes days from 1 to 7; 2nd week includes days from 8 to 14; 3rd week includes days from 15 to 21, 4th week is days from 22 to 28; and 5th week is days from 29 to 31. According to Graph A, regular workers make most of their deposits the second week of each Gregorian month. This dynamic matches salary payments. In fact, regular workers receive their monthly salary within the first week of the following month. Coherently, they make deposits into their savings account mainly on the second week of the month.

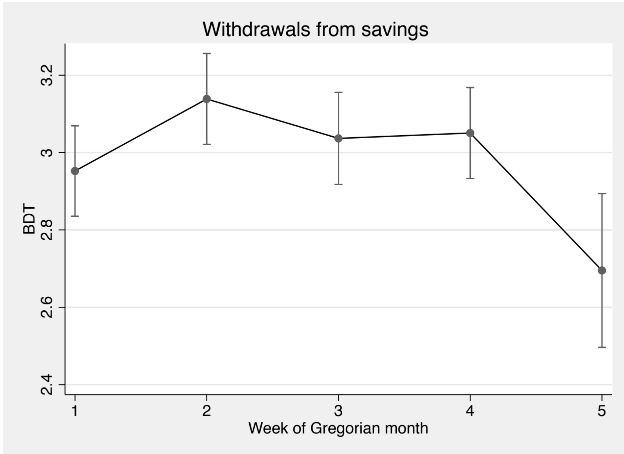
Figure 6

Gregorian week fixed-effects among borrowers

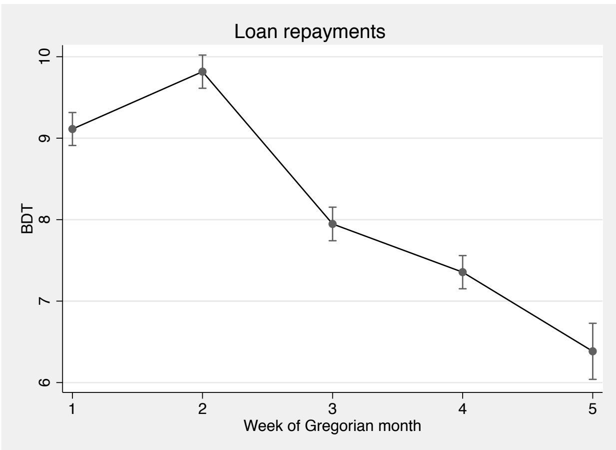
Graph A



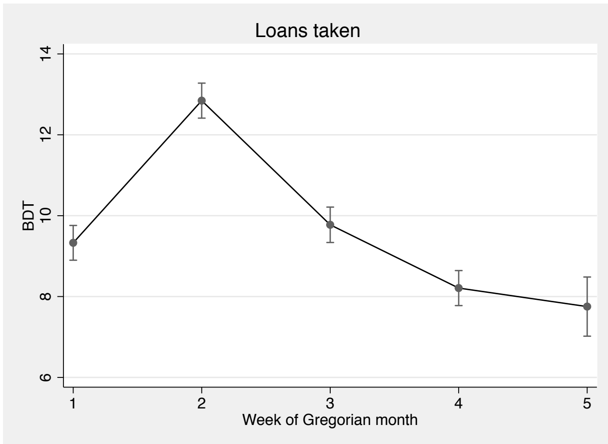
Graph B



Graph C



Graph D

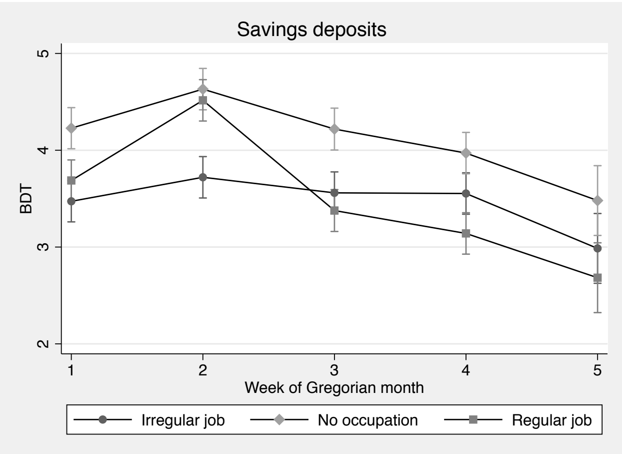


Notes: In Fig. 6, the Graphs A, B, C and D represent the Gregorian week fixed-effects among borrowers. The *x*-axis reports the 1^{st}, 2^{nd}, 3^{rd}, 4^{th} and 5^{th} week of Gregorian months. Weeks are defined as: 1^{st} week includes days from 1 to 7; 2^{nd} week includes days from 8 to 14; 3^{rd} week includes days from 15 to 21, 4^{th} week is days from 22 to 28; and 5^{th} week is days from 29 to 31. The *y*-axis reports the average per-client weekly deposits (Graph A), weekly withdrawals (Graph B), weekly repayments (Graph C) and weekly loans taken (Graph D). Graphs A, C and D show that borrowers increase the account activity on the 2^{nd} week of each Gregorian month. Graph B shows that withdrawals are constant throughout the Gregorian months and decrease the last 3 days of the month.

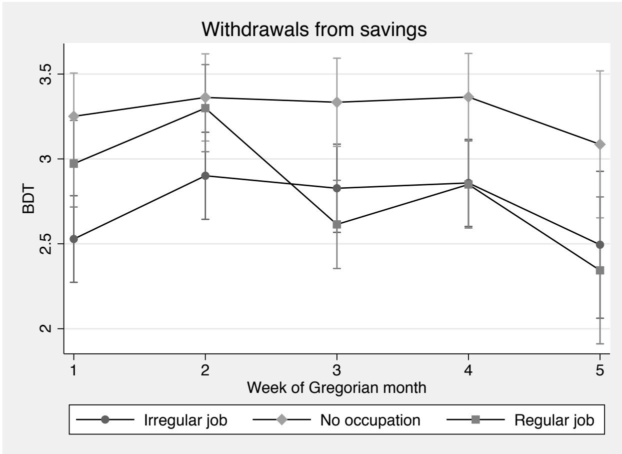
Figure 6bis

Gregorian week fixed-effects among borrowers, by occupational category

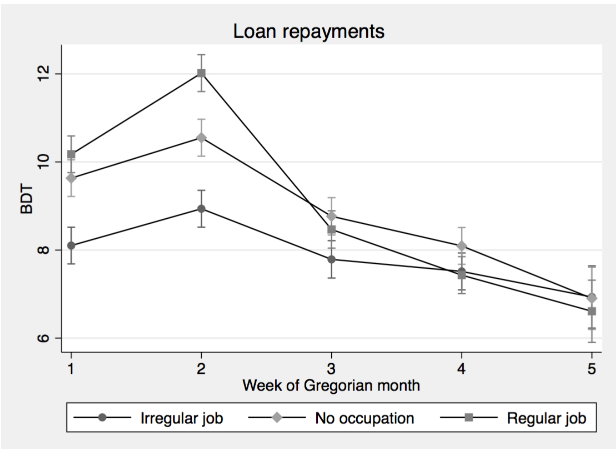
Graph A



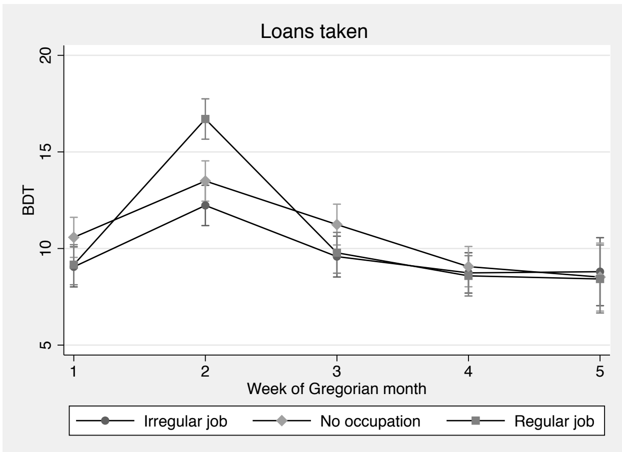
Graph B



Graph C

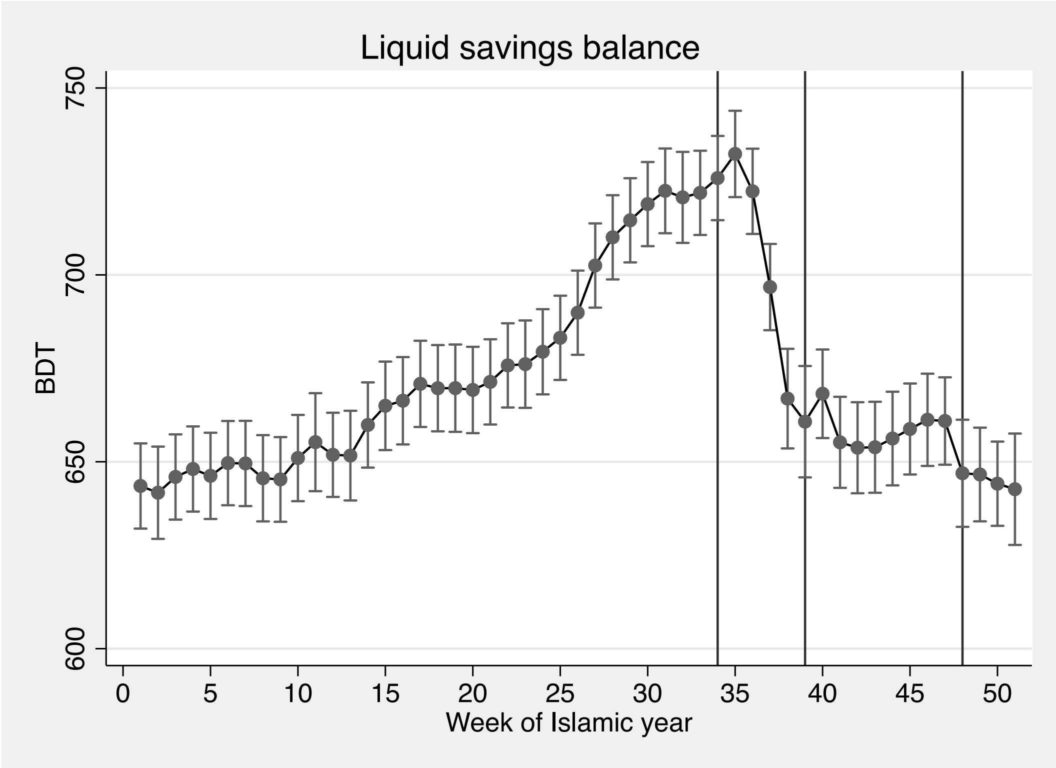


Graph D



Notes: In Fig. 6bis, the Graphs A, B, C and D represent the Gregorian week fixed-effects by occupational category. The *x*-axis reports the 1st, 2nd, 3rd, 4th and 5th week of Gregorian months. Weeks are defined as: 1st week includes days from 1 to 7; 2nd week includes days from 8 to 14; 3rd week includes days from 15 to 21, 4th week is days from 22 to 28; and 5th week is days from 29 to 31. The *y*-axis reports the average per-client weekly deposits (Graph A), weekly withdrawals (Graph B), weekly repayments (Graph C) and weekly loans taken (Graph D). Graphs A, C and D show that (especially) regular workers intensify their account activity on the 2nd week of each Gregorian month.

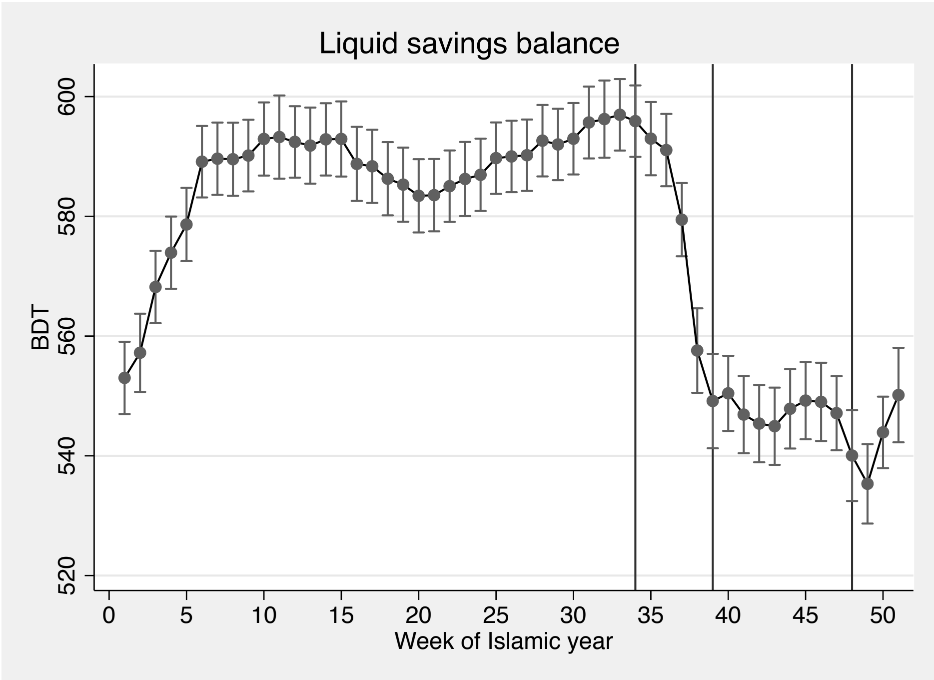
Figure 7
Islamic week fixed-effects among non-borrowers



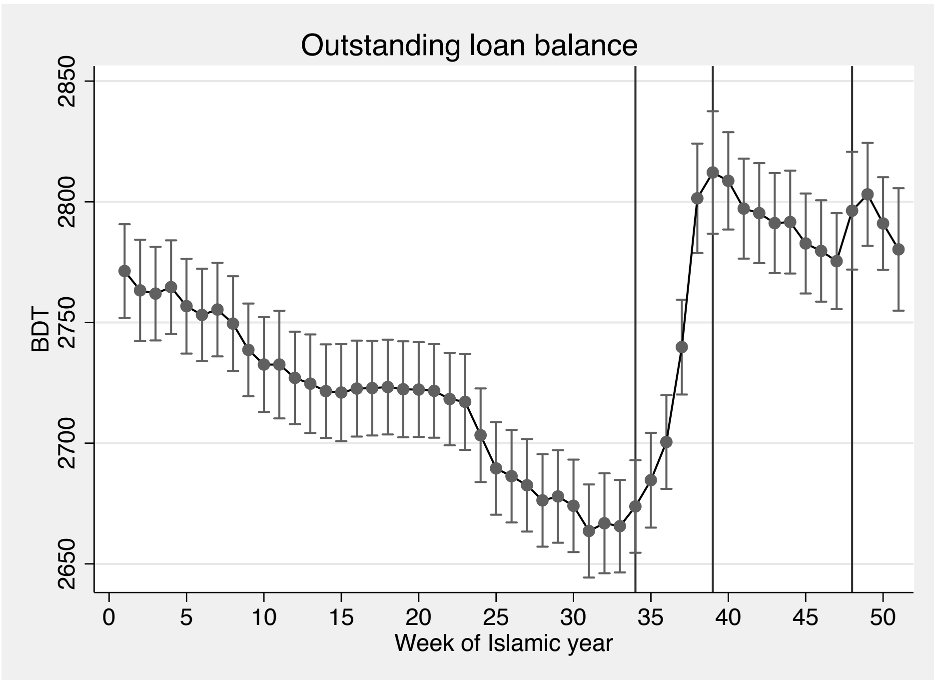
Notes: Fig. 7 displays, for the group of non-borrowers, the Islamic week fixed-effects computed at the sample mean. The *x*-axis reports the 51 weeks of the Islamic calendar. The *y*-axis reports the average per-client weekly savings balances. The vertical lines in the graphs correspond to the three Islamic festivities: month of fasting (*Ramadan*) and end of the month of fasting (*Id al-Fitr*) occurring between weeks 34 to 39; and the date of the Feast of Sacrifice (*Id al-Adha*) occurring in weeks 48 and 49. This analysis shows that savings balances decrease drastically during *Ramadan* and *Id al-Fitr*, and reduce slightly during the *Id al-Adha.*

Figure 8
Islamic week fixed-effects among borrowers

Graph A



Graph B



Notes: Graphs in Fig. 8 display, for the group of borrowers, the Islamic week fixed-effects computed at the sample mean. The *x*-axis reports the 51 weeks of the Islamic calendar. The *y*-axis reports the average per-client weekly savings balance and outstanding loan balance in Graphs A and B, respectively. The vertical lines in the graphs correspond to the three Islamic festivals: month of fasting (*Ramadan*) and end of the month of fasting (*Id al-Fitr*) occurring between weeks 34 to 39; and the date of the Feast of Sacrifice (*Id al-Adha*) occurring in weeks 48 and 49. Graph A shows that liquid savings balances are build rapidly in the first ten weeks of the Islamic year; liquid savings reduce drastically during the three Islamic festivals. Outstanding loan balances (Graph B) decrease through out all the Islamic year, and increase in occasion of the three Islamic festivals.

Table 1
Descriptive statistics

	Global sample (N=10,631)		Non-borrowers (N=2,447)		Borrowers (N=8,184)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Client's characteristics						
Female	0.85	0.36	0.89	0.31	0.83	0.37
Age (in year)	30.87	10.52	28.43	10.90	31.61	10.29
Lenght of time with SafeSave (in year)	1.79	1.37	0.89	0.95	2.06	1.36
Occupational categories:						
irregular job	0.43	-	0.34	-	0.46	-
regular job	0.12	-	0.11	-	0.12	-
no occupation	0.45	-	0.54	-	0.42	-
Location (Safesave branches):						
Gonoktuli	0.19	-	0.19	-	0.19	-
Kurmitola	0.26	-	0.25	-	0.26	-
Millat	0.30	-	0.33	-	0.29	-
Muslim	0.25	-	0.23	-	0.25	-
Financial characteristics						
Total savings balances	1254.20	793.79	604.88	746.68	1448.34	698.64
Outstanding loan balances	2019.75	1705.03	0.00	0.00	2623.66	1480.49
Liquid savings balances	580.95	540.25	604.88	746.68	573.79	460.73
Size of deposits	44.77	78.07	37.68	77.98	46.91	77.98
Size of withdrawals	723.67	765.25	660.51	844.69	741.00	741.10
Loan size (initial amount)	4450.39	1454.06	0.00	0.00	4450.39	1454.06
Size of repayments	235.71	353.03	0.00	0.00	235.71	353.03
# of deposits per day	0.1641	0.1526	0.2427	0.1773	0.1405	0.1358
# of withdrawals per day	0.0065	0.0189	0.0091	0.0145	0.0058	0.0200
# of loans taken per day	0.0019	0.0028	0.0000	0.0000	0.0025	0.0030
# of repayments per day	0.0591	0.0822	0.0000	0.0000	0.0768	0.0862

Notes: As we deal with both time-varying and time-invariant variables and an unbalanced panel dataset, descriptive statistics in Table 1 are computed as follow: first, we attribute to each individual one observation for each characteristic, given by his/her average across time; then we compute the mean, median and standard deviations of the distribution of individuals' average characteristic. All monetary figures are in BDT. BDT 80 = about USD 1.

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Table 2

Trend and seasonality of saving among non-borrowers

Dependent variable	(1) Daily deposits	(2) Daily withdrawals	(3) Daily liquid savings balances	(4) Daily liquid savings balances
Lagged dependent variable				0.992***
				(0.002)
t	-0.003***	-0.001*	0.040***	-0.000
	(0.000)	(0.001)	(0.006)	(0.001)
t-squared	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Days of week				
Sunday	-0.482***	0.169	1.391	
	(0.136)	(0.293)	(2.931)	
Monday	-0.766***	0.272	0.795	-0.771**
	(0.129)	(0.297)	(2.928)	(0.355)
Tuesday	-1.032***	-0.119	1.246	-0.556
	(0.126)	(0.286)	(2.936)	(0.351)
Wednesday	-1.093***	0.217	0.747	-0.850**
	(0.128)	(0.312)	(2.923)	(0.368)
Thursday	-1.356***	0.714**	-0.134	-1.700***
	(0.131)	(0.313)	(2.931)	(0.373)
Weeks of Gregorian month				
Week 2	0.720***	0.042	-2.178	-0.780**
	(0.108)	(0.285)	(2.464)	(0.371)
Week 3	0.427***	-0.421	-2.750	-0.254
	(0.104)	(0.268)	(2.506)	(0.353)
Week 4	0.121	-0.410	-3.770	0.077
	(0.101)	(0.276)	(2.464)	(0.349)
Week 5	-0.155	-1.049***	-0.951	1.082**
	(0.151)	(0.332)	(3.470)	(0.435)
Weeks of Islamic year				
Week 32	1.045***	0.276	77.752***	2.572*
	(0.366)	(1.035)	(8.646)	(1.331)
Week 33	0.949***	0.065	78.961***	2.150*
	(0.292)	(0.993)	(8.288)	(1.279)
Week 34 *(Ramadan)*	0.925***	-0.221	82.902***	3.286***
	(0.312)	(0.932)	(8.376)	(1.176)
Week 35 *(Ramadan)*	0.771***	-0.156	88.822***	2.354**
	(0.287)	(0.931)	(8.532)	(1.196)
Week 36 *(Ramadan)*	0.447*	4.667***	79.373***	-2.702*
	(0.270)	(1.172)	(8.245)	(1.442)
Week 37 *(Ramadan)*	0.936***	5.067***	53.754***	-2.224
	(0.306)	(1.125)	(8.335)	(1.415)
Week 38 *(Ramadan)*	0.651*	7.999***	23.894***	-5.559***
	(0.383)	(1.430)	(9.000)	(1.877)
Week 39 (*Id al-Fitr*)	0.822**	-2.074**	17.742*	3.861***
	(0.411)	(0.956)	(9.802)	(1.278)
Week 40	1.256***	-0.440	25.201***	3.289***
	(0.397)	(0.970)	(8.614)	(1.238)
Week 41	0.216	0.281	12.196	0.197
	(0.307)	(0.964)	(7.814)	(1.216)
Week 46	0.118	-0.717	18.239**	1.773
	(0.306)	(0.916)	(8.543)	(1.123)
Week 47	0.003	-0.107	19.134**	1.338
	(0.271)	(0.967)	(8.752)	(1.246)
Week 48 *(Id al-Adha)*	0.398	5.737***	3.923	-4.281**
	(0.401)	(1.527)	(9.963)	(1.982)
Week 49 *(Id al-Adha)*	0.322	-1.366	3.600	2.743**
	(0.349)	(0.938)	(8.949)	(1.220)
Week 50	0.178	-0.530	1.897	0.994
	(0.305)	(0.951)	(8.222)	(1.341)
Week 51	0.565	-0.450	-0.351	1.068
	(0.369)	(1.119)	(9.888)	(1.437)
Mean of dependent variable	4.48	3.71	672.26	672.26
Observations	7,828	7,828	7,828	6,228
R-squared	0.249	0.061	0.912	0.999
Branch FE	Y	Y	Y	Y

Notes: In Table 2, we run OLS regressions among the group of non-borrowers, at the branch level. From columns (1) to (3), the dependent variable is an aggregate variable at the branch level: column (1), average per-client liquid savings balance; column (2), average per-client deposits into savings; and column (3), average per-client withdrawals from savings. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. BDT 80 = about USD 1.

Table 3
Trend and seasonality of saving and borrowing among borrowers

VARIABLES	(1) Daily deposits	(2) Daily withdrawals	(3) Daily liquid savings balances	(4) Daily liquid savings balances	(5) Daily repayments	(6) Daily loans taken	(7) Daily outstanding loan balances	(8) Daily outstanding loan balances
Lagged dependent variable				0.993***				0.992***
				(0.002)				(0.002)
t	-0.003***	-0.001***	0.038***	0.001**	-0.004***	-0.008***	0.140***	-0.002**
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.001)	(0.014)	(0.001)
t-squared	0.000***	0.000***	0.000***	0.000**	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Days of week								
Sunday	-0.535***	-0.417***	0.129		-1.796***	5.572***	1.894	
	(0.083)	(0.101)	(1.544)		(0.178)	(0.374)	(4.994)	
Monday	-0.702***	-0.395***	-0.402	0.228	-2.056***	4.135***	2.344	-1.812***
	(0.084)	(0.100)	(1.550)	(0.175)	(0.182)	(0.344)	(4.994)	(0.462)
Tuesday	-0.798***	-0.354***	-0.712	0.420**	-2.185***	3.343***	3.334	-2.547***
	(0.081)	(0.109)	(1.541)	(0.170)	(0.187)	(0.328)	(4.920)	(0.457)
Wednesday	-0.712***	-0.389***	-0.383	0.475***	-2.167***	3.432***	3.051	-2.353***
	(0.084)	(0.102)	(1.542)	(0.171)	(0.186)	(0.324)	(4.941)	(0.461)
Thursday	-1.293***	-0.260***	-1.999	-0.771***	-2.902***	4.328***	5.618	-0.915**
	(0.079)	(0.100)	(1.539)	(0.172)	(0.178)	(0.337)	(4.965)	(0.456)
Weeks of Gregorian month								
Week 2	0.402***	0.186**	-0.428	-1.086***	0.704***	3.516***	1.749	2.084***
	(0.071)	(0.084)	(1.322)	(0.168)	(0.166)	(0.350)	(4.284)	(0.445)
Week 3	-0.022	0.084	-2.283*	-0.922***	-1.165***	0.446	1.950	0.600
	(0.069)	(0.083)	(1.312)	(0.155)	(0.160)	(0.301)	(4.259)	(0.414)
Week 4	-0.313***	0.098	-4.757***	-0.674***	-1.757***	-1.119***	0.448	0.270
	(0.067)	(0.083)	(1.313)	(0.150)	(0.158)	(0.287)	(4.228)	(0.397)
Week 5	-0.703***	-0.257**	-5.499***	-0.502***	-2.729***	-1.577***	1.245	0.838
	(0.079)	(0.118)	(1.858)	(0.191)	(0.200)	(0.384)	(5.991)	(0.520)
Weeks of Islamic year								
Week 32	0.130	-0.244	44.881***	-0.058	0.482	0.921	-104.502***	2.273**
	(0.209)	(0.249)	(4.764)	(0.455)	(0.491)	(0.903)	(16.233)	(1.138)
Week 33	0.309	0.261	45.558***	0.362	1.099**	2.187**	-105.710***	1.002
	(0.204)	(0.248)	(4.668)	(0.464)	(0.441)	(0.934)	(15.372)	(1.234)
Week 34 *(Ramadan)*	0.286	0.080	44.453***	-0.522	1.236***	4.910***	-97.548***	3.910***
	(0.203)	(0.254)	(4.760)	(0.456)	(0.379)	(1.007)	(15.180)	(1.208)
Week 35 *(Ramadan)*	0.521**	0.199	41.337***	-0.178	1.679***	3.978***	-86.656***	2.583**
	(0.214)	(0.254)	(4.888)	(0.456)	(0.428)	(0.905)	(15.201)	(1.072)
Week 36 *(Ramadan)*	0.833***	0.467*	39.679***	-1.050**	2.024***	6.845***	-70.843***	6.405***
	(0.209)	(0.271)	(4.903)	(0.517)	(0.432)	(1.085)	(15.310)	(1.285)
Week 37 *(Ramadan)*	1.389***	1.343***	28.038***	-2.952***	4.105***	13.468***	-31.515**	12.446***
	(0.229)	(0.302)	(4.884)	(0.608)	(0.552)	(1.311)	(15.350)	(1.548)
Week 38 *(Ramadan)*	1.275***	2.527***	6.139	-6.533***	4.858***	21.099***	30.116*	19.560***
	(0.271)	(0.348)	(5.233)	(0.780)	(0.531)	(1.646)	(16.432)	(2.144)
Week 39 (*Id al-Fitr*)	-0.477**	-1.037***	-2.237	1.797***	0.300	-3.522***	40.837**	-1.653
	(0.233)	(0.254)	(5.691)	(0.519)	(0.510)	(0.924)	(17.493)	(1.348)
Week 40	-0.038	0.084	-0.984	-0.462	-0.037	1.399*	37.354**	2.009*
	(0.203)	(0.284)	(5.071)	(0.442)	(0.392)	(0.841)	(16.173)	(1.158)
Week 41	0.210	-0.229	-4.553	-0.495	0.243	2.170**	25.862*	2.440*
	(0.211)	(0.259)	(4.630)	(0.480)	(0.383)	(0.965)	(15.292)	(1.259)
Week 46	0.324	-0.024	-2.367	0.196	0.455	1.074	8.312	1.477
	(0.220)	(0.260)	(4.635)	(0.412)	(0.407)	(0.841)	(15.393)	(1.009)
Week 47	0.261	0.273	-4.191	-1.295**	1.312***	4.803***	4.071	5.154***
	(0.214)	(0.272)	(4.948)	(0.508)	(0.398)	(1.056)	(18.792)	(1.374)
Week 48 *(Id al-Adha)*	1.536***	2.149***	-11.352**	-5.872***	3.801***	15.499***	24.989	14.283***
	(0.525)	(0.377)	(5.757)	(0.897)	(0.644)	(2.046)	(22.246)	(2.582)
Week 49 *(Id al-Adha)*	-0.499**	-0.767***	-16.092***	0.934**	-0.601	-3.697***	31.755	-1.291
	(0.210)	(0.251)	(5.331)	(0.471)	(0.377)	(0.810)	(19.529)	(1.110)
Week 50	-0.134	-0.151	-8.834*	0.140	-0.423	-0.383	19.695	0.629
	(0.200)	(0.251)	(4.943)	(0.386)	(0.348)	(0.776)	(18.631)	(1.075)
Week 51	-0.213	0.070	-1.253	-0.085	0.394	0.338	8.943	-1.220
	(0.239)	(0.303)	(6.014)	(0.514)	(0.446)	(0.989)	(22.825)	(1.427)
Mean of dependent variable	2.98	2.43	576.97	576.97	6.74	7.92	2,738.96	2,738.96
Observations	7,829	7,829	7,829	6,228	7,829	7,829	7,829	6,228
R-squared	0.226	0.087	0.968	1.000	0.271	0.249	0.891	0.999
Branch FE	Y	Y	Y	Y	Y	Y	Y	Y

Notes: In Table 3, we run OLS regressions among the group of borrowers, at the branch level. From columns (1) to (6), the dependent variable is an aggregate variable at the branch level: in column (1), average per-client liquid savings balances; in columns (2), average per-client deposits into savings; and in column (3), average per-client withdrawals from savings; column (4), average per-client outstanding loan balance; column (5), average per-client loan repayments; and column (6), average per-client loans taken. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. BDT 80 = about USD 1.

Table 4
Reaction to *Hartal* among Non-borrowers

	(1)	(2)	(3)	(4)
Sample	Non borrowers	Non borrowers	Non borrowers	Non borrowers
Dependent variable	Daily deposits	Daily withdrawals	Change in savings balance	Deposits minus withdrawals
5 days befoer H	1.10**	0.33	0.39	0.77
	(0.52)	(1.21)	(1.55)	(1.26)
4 days befoer H	-0.02	-0.04	-0.79	0.02
	(0.55)	(0.91)	(1.31)	(0.94)
3 days before H	-0.08	2.17**	-2.13*	-2.26**
	(0.35)	(0.97)	(1.24)	(0.97)
2 days before H	-0.51	-1.60**	0.99	1.08
	(0.42)	(0.63)	(0.97)	(0.70)
1 day before H	-0.41	-0.44	-0.83	0.04
	(0.30)	(0.68)	(1.06)	(0.73)
1st day of H	-0.52**	0.39	-0.04	-0.91
	(0.24)	(0.82)	(0.90)	(0.85)
2dn, 3rd days of H	-0.83*	1.20	-2.73	-2.03
	(0.47)	(1.42)	(1.85)	(1.30)
1 day after H	-0.86***	0.57	-1.29	-1.43
	(0.23)	(0.93)	(1.08)	(0.98)
2 days after H	-0.08	0.44	-0.41	-0.52
	(0.34)	(1.22)	(1.74)	(1.22)
3 days after H	0.22	0.53	-0.84	-0.31
	(0.36)	(0.95)	(1.35)	(1.05)
4 days after H	-0.04	-0.03	1.15	-0.01
	(0.54)	(0.81)	(1.23)	(0.97)
5 days after H	0.19	-1.86***	0.66	2.05***
	(0.45)	(0.51)	(0.79)	(0.62)
Mean value of dependent variable	-0.0247	-0.0371	0.0000	0.0124
Observations	7,828	7,828	6,228	7,828
R-squared	0.00	0.00	0.00	0.00

Notes: OLS regressions among the group of non-borrowers. Outcome variables, $\bar{\eta}_{bt}$, are the branch-level residuals of Eq. (1), $Y_{bt} = \beta_{t^g} + \gamma_{t^i} + \alpha_b + T_{bt} + \eta_{bt}$, where Y_{bt} is: in column (1), average per-client deposits into savings; in column (2), average per-client withdrawals from savings; and in column (3), average per-client change in savings balances. In column (4), the outcome variable is the residuals of deposits minus the residuals of withdrawals. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. BDT 80 = about USD 1.

Table 4bis
Reaction to *Hartal* among Non-borrowers

	(1)	(2)	(3)	(4)
Sample	Non borrowers	Non borrowers	Non borrowers	Non borrowers
Dependent variable	Daily deposits	Daily withdrawals	Change in savings balance	Deposits minus withdrawals
5 days befoer H	1.14**	0.43	0.28	0.71
	(0.53)	(1.23)	(1.58)	(1.28)
4 days befoer H	0.02	0.06	-0.89	-0.04
	(0.55)	(0.94)	(1.33)	(0.97)
3 days before H	-0.04	2.27**	-2.23*	-2.31**
	(0.37)	(1.00)	(1.27)	(1.00)
2 days before H	-0.47	-1.49**	0.88	1.02
	(0.43)	(0.68)	(1.02)	(0.75)
1 day before H	-0.37	-0.35	-0.94	-0.02
	(0.32)	(0.71)	(1.10)	(0.77)
1st day of H	-0.48*	0.50	-0.15	-0.98
	(0.26)	(0.86)	(0.96)	(0.89)
2dn, 3rd days of H	-0.79	1.31	-2.84	-2.09
	(0.49)	(1.44)	(1.88)	(1.33)
1 day after H	-0.82***	0.67	-1.40	-1.49
	(0.25)	(0.96)	(1.12)	(1.01)
2 days after H	-0.05	0.53	-0.51	-0.57
	(0.36)	(1.23)	(1.75)	(1.23)
3 days after H	0.26	0.63	-0.94	-0.38
	(0.38)	(0.98)	(1.38)	(1.08)
4 days after H	-0.01	0.06	1.05	-0.07
	(0.54)	(0.84)	(1.27)	(1.00)
5 days after H	0.23	-1.76***	0.54	1.98***
	(0.47)	(0.57)	(0.85)	(0.67)
Mean value of dependent variable	-0.1749	-0.0039	-0.1528	-0.1710
Observations	1,688	1,688	1,356	1,688
R-squared	0.01	0.01	0.01	0.01

Notes: OLS regressions among the group of non-borrowers. The estimation period includes the 10 days before and the 10 days after the hartal events. Outcome variables, $\bar{\eta}_{bt}$, are the branch-level residuals of Eq. (1), $Y_{bt} = \beta_{t^g} + \gamma_{t^i} + \alpha_b + T_{bt} + \eta_{bt}$, where Y_{bt} is: in column (1), average per-client deposits into savings; in column (2), average per-client withdrawals from savings; and in column (3), average per-client change in savings balances. In column (4), the outcome variable is the residuals of deposits minus the residuals of withdrawals. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. BDT 80 = about USD 1.

Table 5

Reaction to *Hartal* among Borrowers

Saving behavior

	(1)	(2)	(3)	(4)
Sample	Borrowers	Borrowers	Borrowers	Borrowers
Dependent variable	Daily deposits	Daily withdrawals	Change in savings balance	Deposits minus withdrawals
5 days before H	0.40*	0.03	0.13	0.38
	(0.23)	(0.36)	(0.67)	(0.43)
4 days before H	-0.12	-0.50**	0.29	0.38
	(0.23)	(0.23)	(0.55)	(0.36)
3 days before H	0.15	0.03	-0.23	0.11
	(0.24)	(0.27)	(0.42)	(0.36)
2 days before H	-0.19	-0.05	-0.68	-0.14
	(0.26)	(0.29)	(0.47)	(0.29)
1 day before H	-0.21	-0.24	-0.45	0.03
	(0.19)	(0.22)	(0.43)	(0.31)
1st day of H	0.26	-0.05	0.16	0.31
	(0.24)	(0.22)	(0.30)	(0.28)
2dn, 3rd days of H	-0.50*	-0.04	-0.59	-0.46
	(0.26)	(0.35)	(0.66)	(0.45)
1 day after H	-0.23	0.04	-0.46	-0.28
	(0.21)	(0.30)	(0.39)	(0.36)
2 days after H	0.41	-0.11	0.41	0.52
	(0.27)	(0.23)	(0.37)	(0.32)
3 days after H	0.19	-0.49*	0.17	0.68**
	(0.24)	(0.27)	(0.38)	(0.32)
4 days after H	-0.03	0.02	0.12	-0.05
	(0.28)	(0.29)	(0.45)	(0.39)
5 days after H	0.08	-0.12	-0.37	0.20
	(0.25)	(0.27)	(0.35)	(0.37)
Mean value of dependent variable	-0.0159	-0.0150	0.0000	-0.0010
Observations	7,829	7,829	6,228	7,829
R-squared	0.00	0.00	0.00	0.00

Notes: OLS regressions among the group of borrowers. From columns (1) to (4), outcome variables, $\bar{\eta}_{bt}$, are the branch-level residuals of Eq. (1), $Y_{bt} = \beta_{t^g} + \gamma_{t^i} + \alpha_b + T_{bt} + \eta_{bt}$, where Y_{bt} is: in column (1), average per-client deposits into savings; in column (2), average per-client withdrawals from savings; and in column (3), average per-client change in savings balances. In column (4), the outcome variable is the residuals of deposits minus the residuals of withdrawals. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. 80 BDT = about 1 USD.

Table 5bis

Reaction to *Hartal* among Borrowers

Saving behavior

	(1)	(2)	(3)	(4)
Sample	Borrowers	Borrowers	Borrowers	Borrowers
Dependent variable	Daily deposits	Daily withdrawals	Change in savings balance	Deposits minus withdrawals
5 days befoer H	0.24	-0.05	0.28	0.29
	(0.25)	(0.37)	(0.68)	(0.45)
4 days befoer H	-0.27	-0.56**	0.43	0.29
	(0.24)	(0.25)	(0.56)	(0.38)
3 days before H	-0.01	-0.03	-0.08	0.02
	(0.26)	(0.28)	(0.43)	(0.38)
2 days before H	-0.37	-0.13	-0.52	-0.24
	(0.28)	(0.31)	(0.49)	(0.32)
1 day before H	-0.37*	-0.31	-0.29	-0.05
	(0.21)	(0.24)	(0.46)	(0.33)
1st day of H	0.09	-0.13	0.32	0.22
	(0.26)	(0.24)	(0.33)	(0.31)
2dn, 3rd days of H	-0.68**	-0.12	-0.43	-0.56
	(0.28)	(0.36)	(0.68)	(0.47)
1 day after H	-0.40*	-0.03	-0.30	-0.37
	(0.23)	(0.31)	(0.42)	(0.38)
2 days after H	0.27	-0.17	0.55	0.45
	(0.28)	(0.24)	(0.39)	(0.34)
3 days after H	0.03	-0.56**	0.33	0.59*
	(0.25)	(0.28)	(0.41)	(0.35)
4 days after H	-0.18	-0.05	0.27	-0.13
	(0.30)	(0.30)	(0.47)	(0.40)
5 days after H	-0.09	-0.19	-0.21	0.10
	(0.27)	(0.29)	(0.38)	(0.39)
Mean value of dependent variable	0.0893	0.0220	-0.1231	0.0672
Observations	1,688	1,688	1,356	1,688
R-squared	0.01	0.00	0.00	0.00

Notes: OLS regressions among the group of borrowers. The estimation period include the 10 days before and the 10 days after the hartal events. From columns (1) to (4), outcome variables, $\bar{\eta}_{bt}$, are the branch-level residuals of Eq. (1), $Y_{bt} = \beta_{t^g} + \gamma_{t^i} + \alpha_b + T_{bt} + \eta_{bt}$, where Y_{bt} is: in column (1), average per-client deposits into savings; in column (2), average per-client withdrawals from savings; and in column (3), average per-client change in savings balances. In column (4), the outcome variable is the residuals of deposits minus the residuals of withdrawals. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. 80 BDT = about 1 USD.

Table 6
Reaction to *Hartal* among Borrowers
Borrowing behavior

	(1)	(2)	(3)	(4)
Sample	Borrowers	Borrowers	Borrowers	Borrowers
Dependent variable	Daily loan repayments	Daily loans taken	Change in outstanding loan	Loans taken minus repayment
5 days before H	0.24	-0.32	-1.43	-0.56
	(0.51)	(1.05)	(1.59)	(1.00)
4 days before H	-0.50	-2.04**	-1.75	-1.54
	(0.49)	(1.03)	(1.54)	(1.08)
3 days before H	-0.58	-0.95	-1.47	-0.37
	(0.41)	(0.96)	(0.96)	(0.97)
2 days before H	-0.89*	0.86	1.07	1.75
	(0.48)	(1.37)	(1.72)	(1.28)
1 day before H	-0.83*	-1.98**	-2.17*	-1.15
	(0.43)	(0.82)	(1.22)	(0.89)
1st day of H	0.35	-1.49	-2.30**	-1.85**
	(0.46)	(0.93)	(1.14)	(0.94)
2dn, 3rd days of H	-0.71	0.55	0.54	1.26
	(0.69)	(2.13)	(1.98)	(1.79)
1 day after H	-0.70	0.63	0.64	1.33
	(0.53)	(1.37)	(1.49)	(1.45)
2 days after H	0.61	0.11	0.29	-0.50
	(0.54)	(0.88)	(1.31)	(0.92)
3 days after H	0.32	1.75	1.94	1.43
	(0.59)	(1.21)	(1.63)	(1.38)
4 days after H	0.06	0.98	2.04	0.92
	(0.53)	(1.47)	(1.83)	(1.55)
5 days after H	0.82	-1.47	-1.62	-2.29**
	(0.50)	(0.95)	(1.34)	(1.07)
Mean value of dependent variable	-0.0645	0.1879	0.0000	0.2524
Observations	7,829	7,829	6,228	7,829
R-squared	0.00	0.00	0.00	0.00

Notes: OLS regressions among the group of borrowers. From columns (1) to (4), outcome variables, $\bar{\eta}_{bt}$, are the branch-level residuals of Eq. (1), $Y_{bt} = \beta_{t^g} + \gamma_{t^i} + \alpha_b + T_{bt} + \eta_{bt}$, where Y_{bt} is: in column (1), average per-client loan repayments; in column (2), average per-client loans taken; in column (3), average per-client change in outstanding loan balances. In column (4), the outcome variable is the residuals of loans taken minus repayments. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. BDT 80 = about USD 1.

Table 6bis
Reaction to *Hartal* among Borrowers
Borrowing behavior

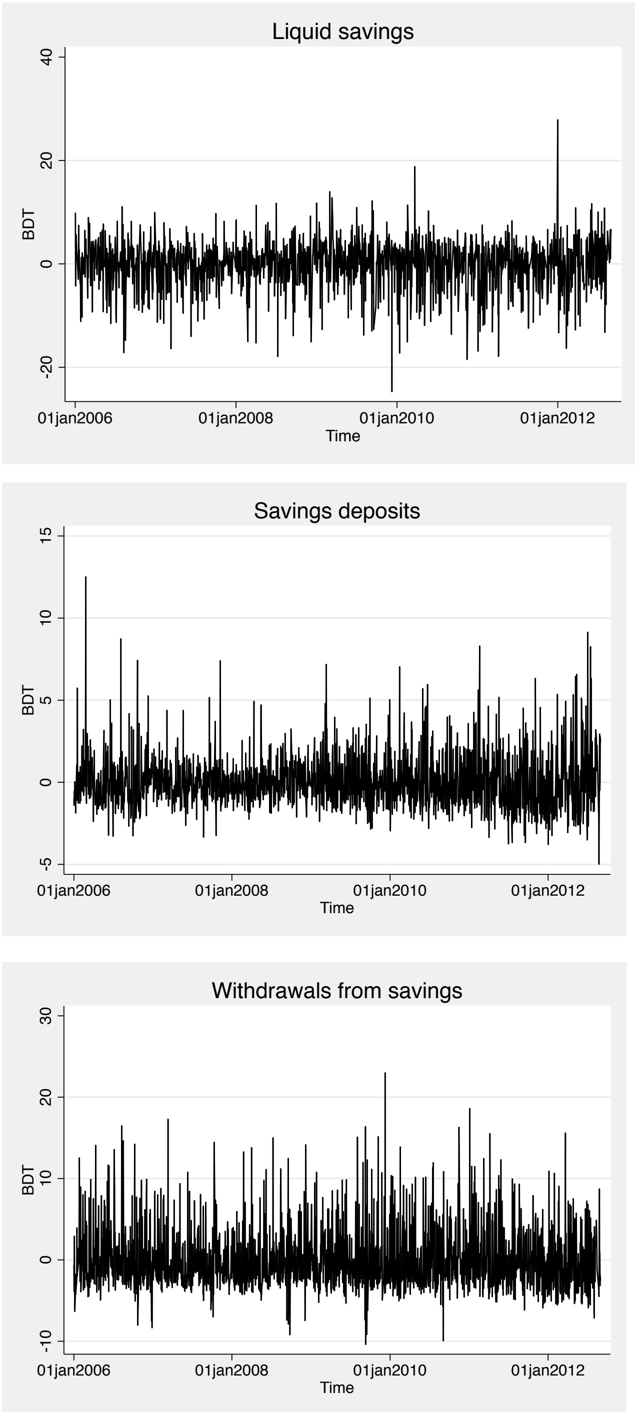
	(1)	(2)	(3)	(4)
Sample	Borrowers	Borrowers	Borrowers	Borrowers
Dependent variable	Daily loan repayments	Daily loans taken	Change in outstanding loan	Loans taken minus repayment
5 days before H	0.27	-1.20	-1.83	-1.47
	(0.54)	(1.12)	(1.65)	(1.08)
4 days before H	-0.47	-2.87***	-2.12	-2.39**
	(0.51)	(1.09)	(1.60)	(1.13)
3 days before H	-0.55	-1.79*	-1.85*	-1.24
	(0.43)	(1.03)	(1.06)	(1.04)
2 days before H	-0.85*	-0.05	0.65	0.80
	(0.50)	(1.43)	(1.79)	(1.35)
1 day before H	-0.81*	-2.81***	-2.59**	-2.01**
	(0.45)	(0.89)	(1.32)	(0.96)
1st day of H	0.38	-2.41**	-2.72**	-2.80***
	(0.49)	(1.01)	(1.25)	(1.03)
2dn, 3rd days of H	-0.68	-0.37	0.12	0.31
	(0.71)	(2.17)	(2.05)	(1.84)
1 day after H	-0.67	-0.25	0.23	0.42
	(0.55)	(1.42)	(1.56)	(1.50)
2 days after H	0.64	-0.65	-0.08	-1.29
	(0.56)	(0.94)	(1.38)	(0.98)
3 days after H	0.35	0.87	1.54	0.52
	(0.61)	(1.26)	(1.69)	(1.43)
4 days after H	0.09	0.16	1.65	0.07
	(0.55)	(1.51)	(1.89)	(1.58)
5 days after H	0.85	-2.39**	-2.05	-3.24***
	(0.53)	(1.04)	(1.43)	(1.15)
Mean value of dependent variable	-0.1462	0.7535	-0.0102	0.8997
Observations	1,688	1,688	1,356	1,688
R-squared	0.01	0.01	0.01	0.01

Notes: OLS regressions among the group of borrowers. The estimation period include the 10 days before and the 10 days after the hartal events. From columns (1) to (4), outcome variables, $\bar{\eta}_{bt}$, are the branch-level residuals of Eq. (1), $Y_{bt} = \beta_{t^g} + \gamma_{t^i} + \alpha_b + T_{bt} + \eta_{bt}$, where Y_{bt} is: in column (1), average per-client loan repayments; in column (2), average per-client loans taken; in column (3), average per-client change in outstanding loan balances. In column (4), the outcome variable is the residuals of loans taken minus repayments. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. BDT 80 = about USD 1.

Appendix

A. Plot of residuals

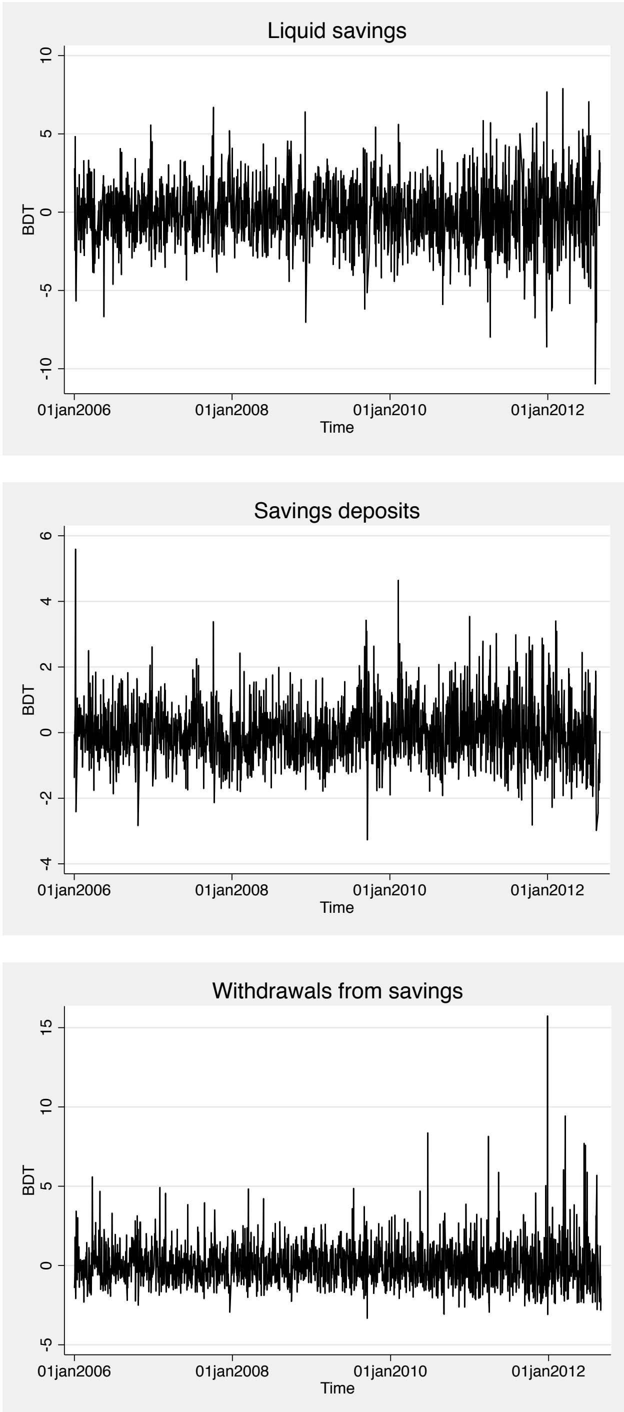
Figure A1
Residuals of savings balances, deposits and withdrawals among non-borrowers



Note: For savings balances, residuals of the OLS regression that includes a quadratic trend, seasonality and lagged value of dependent variable. For savings deposits and withdrawals, residuals of the OLS regression including a quadratic trend and seasonality.

Figure A2

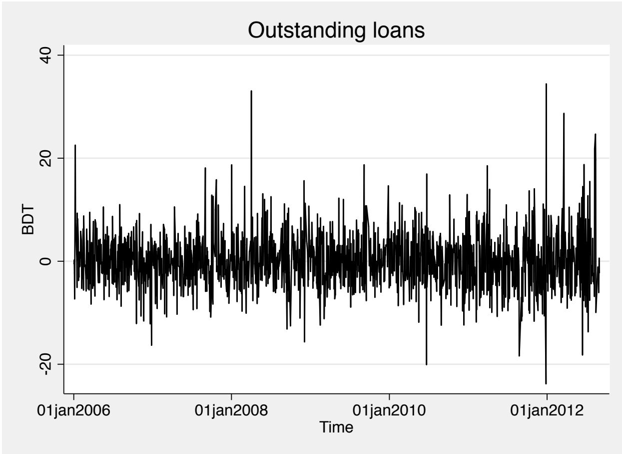
Residual of savings balances, deposits and withdrawals among borrowers

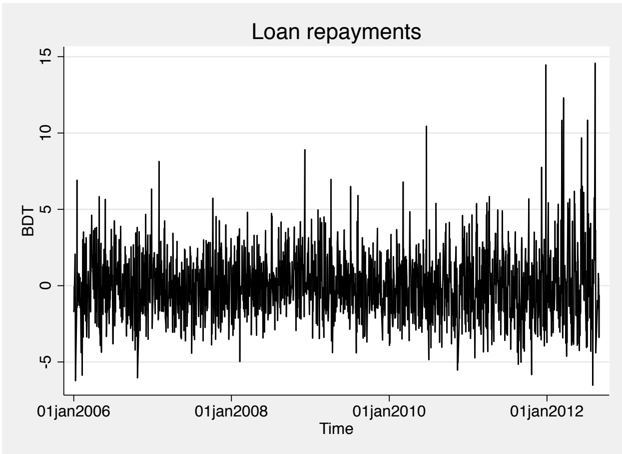


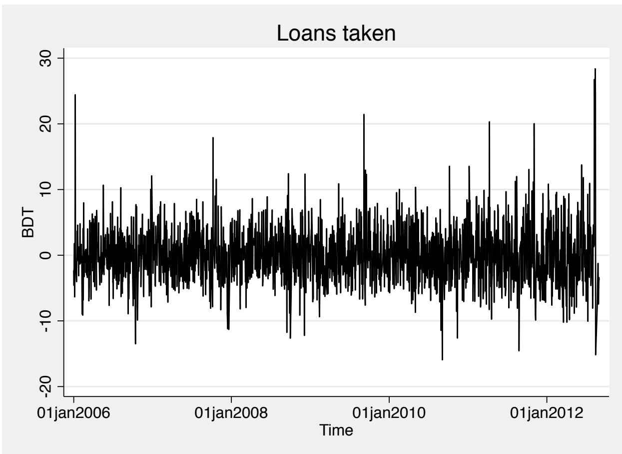
Note: For savings balances, residuals of the OLS regression that includes a quadratic trend, seasonality and lagged value of dependent variable. For savings deposits and withdrawals, residuals of the OLS regression including a quadratic trend and seasonality.

Table A3

Residuals of outstanding loan balances, repayments and loans taken among borrowers







Note: For outstanding loan balances, residuals of the OLS regression that includes a quadratic trend, seasonality and lagged value of dependent variable. For loan repayments and loans taken, residuals of the OLS regression including a quadratic trend and seasonality.

B. Professional Occupations

Table B1
Occupational Categories

Occupation categories	Freq.	Percent
Unemployed		
NO occupation	10	0.09
child/student	301	2.83
housewife	4,415	41.53
Regular job		
job	261	2.46
cooker, resto/hotel worker, guard	20	0.19
teacher, medical staff	59	0.55
factory worker (garments or other)	207	1.95
domestic servant	73	0.69
service	643	6.05
Irregular jobs		
electrician, mechanic, engeneer	16	0.15
business, (street) trader	706	6.64
craft worker	3,094	29.1
manual laborer	8	0.08
rickshaw puller	82	0.77
shop owner/shop worker	109	1.03
worker	568	5.34
Not available	59	0.55
Total	**10,631**	**100**

Note: The table describes the occupational categories in our sample.

C. List of Hartal Days

2006
15 Feb 2006
2 Mar 2006
13 Mar 2006
20 Apr 2006
23 Apr 2006
13 Jun 2006 – First day
14 Jun 2006 – Second (consecutive) day
4 Jul 2006
15 Aug 2006
30 Aug 2006
10 Sep 2006
21 Sep 2006
21 Dec 2006

2007
7 Jan2007 – First day
8 Jan2007 – Second day
9 Jan2007 – Third day

2010
27 Jun 2010
14 Nov 2010
30 Nov 2010

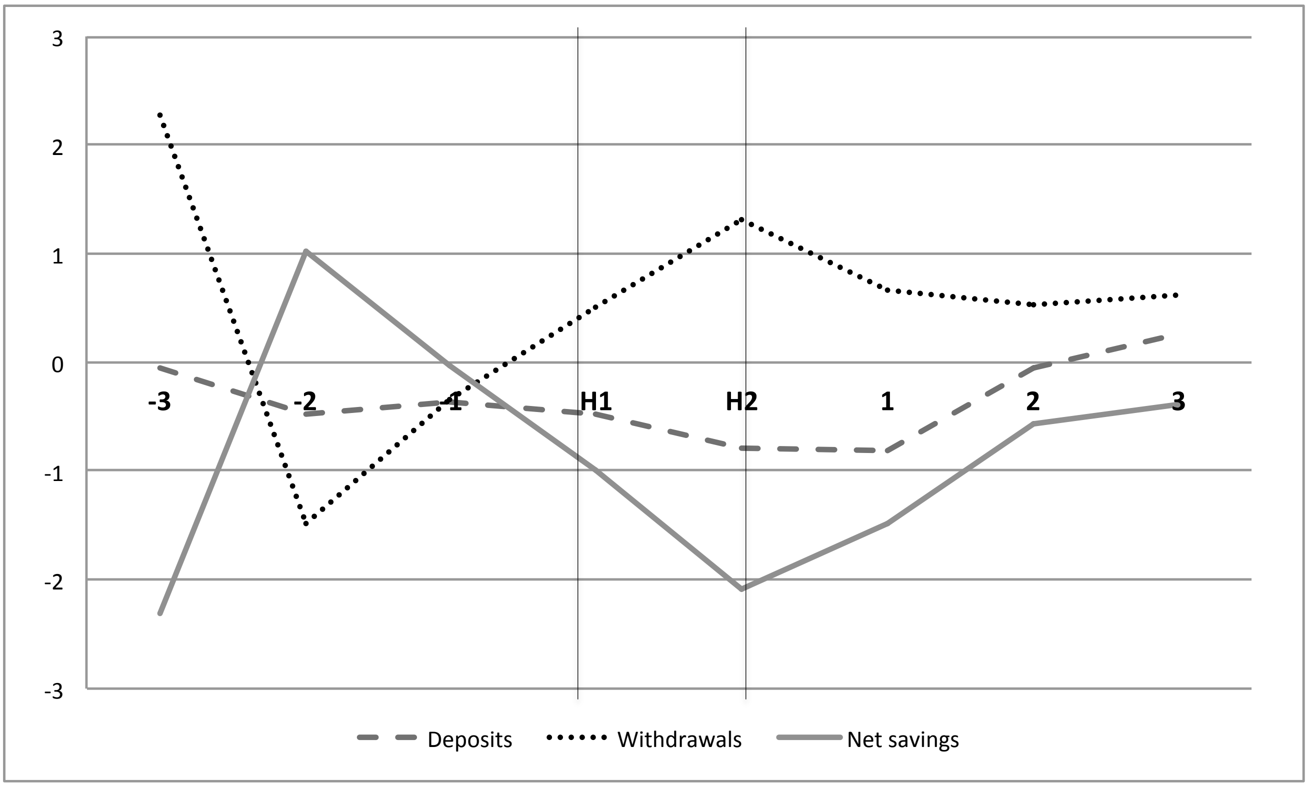
2011
7 Feb 2011
4 Apr 2011
5 Jun 2011
12 Jun 2011 – First day
13 Jun 2011 – Second day
6 Jul 2011 – First day
7 Jul 2011– Second day
10 Jul 2011 – First day
11 Jul 2011 – Second day
22 Sep 2011
4 Dec 2011

2012
22 Apr 2012 – First day
23 Apr 2012 – Second day
24 Apr 2012 – Third day
29 Apr 2012 – First day
30 Apr 2012 – Second day
17 May 2012

Notes: The severe hartal events—i.e. two or more consecutive hartal days—are highlighted in red. The hartal of January 1, 2006, is not included in the analysis.

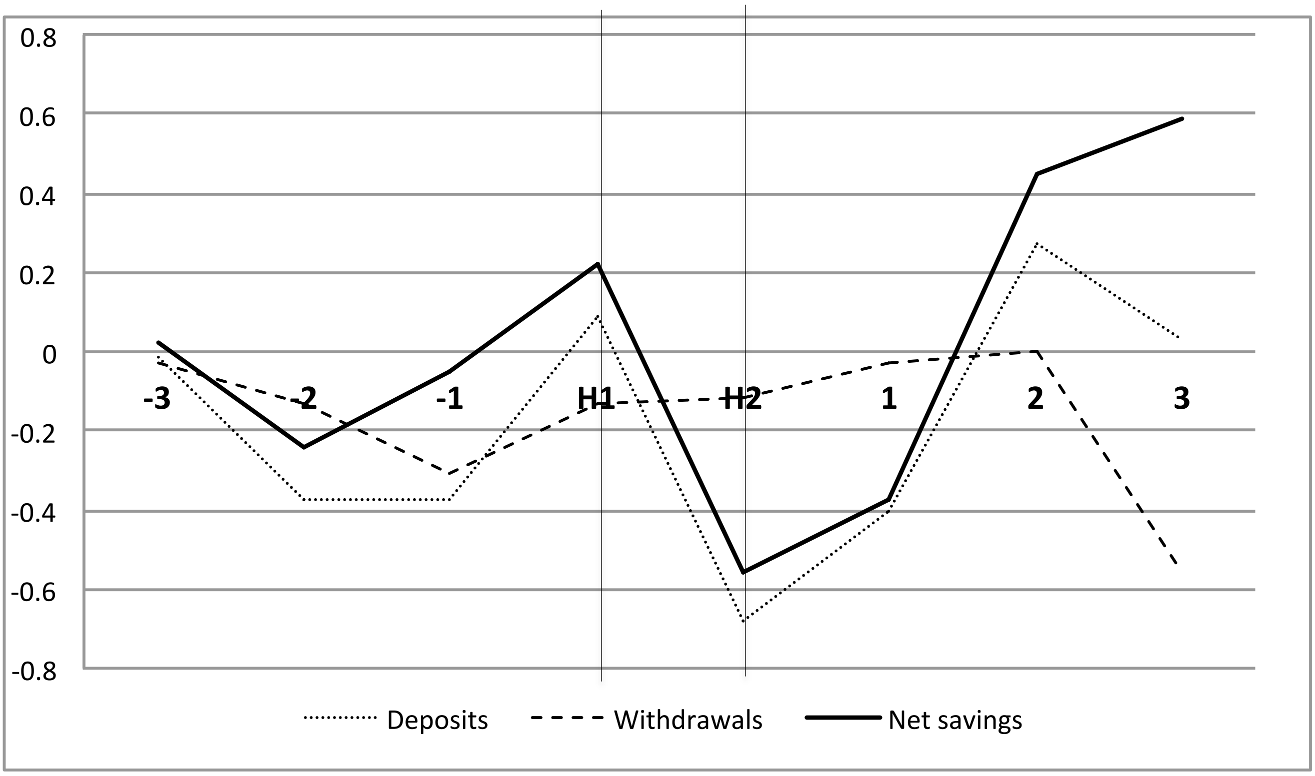
D. Hartal effect

Figure D1
Hartal effect among non-borrowers



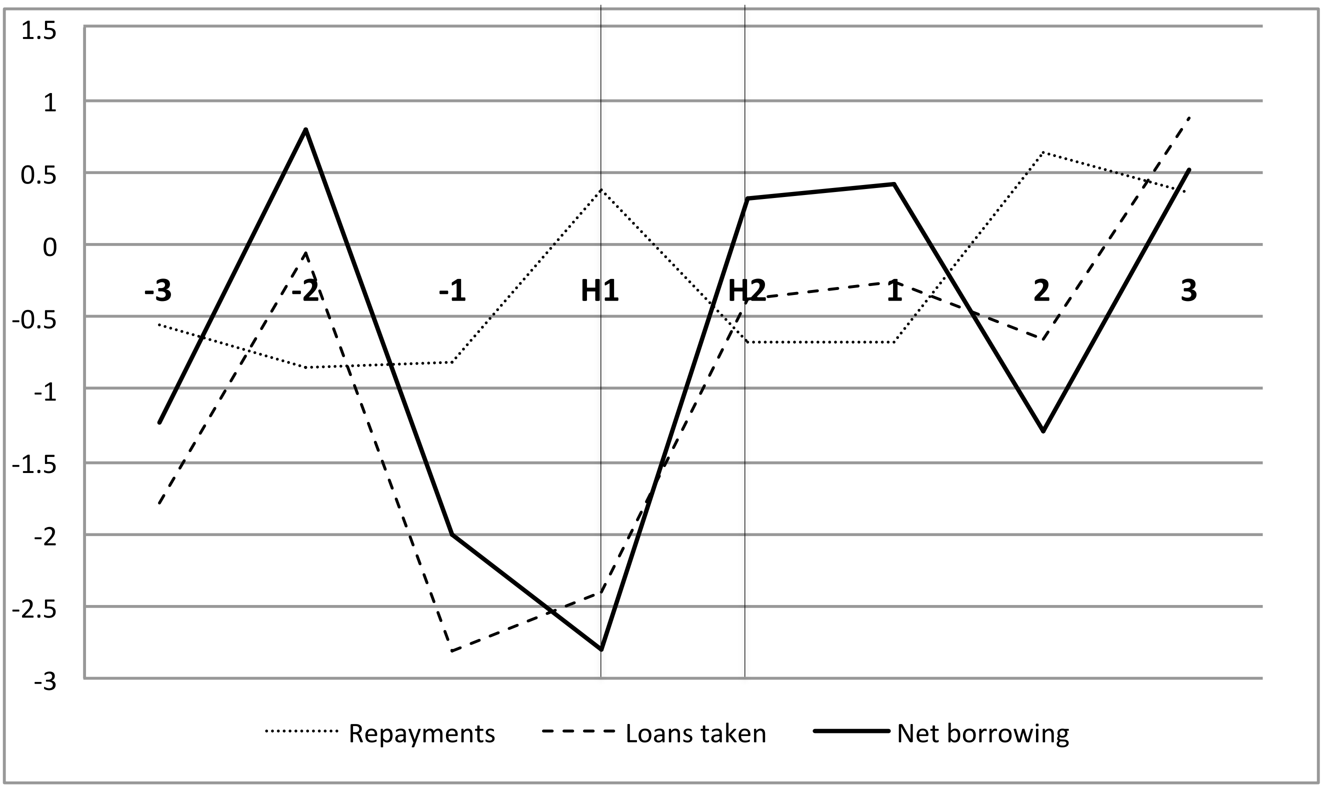
Notes: Graph in Fig. D1 reports, for the group of non-borrowers, the estimated coefficients of the *hartal* regression in Eq. (2) (precisely, the estimated coefficients displayed in Table 4bis). The two vertical lines delimitate the hartal event: "H1" indicate the first day of hartal; "H2" indicates hartal days that follow (and are consecutive to) the first one. Net savings is deposits minus withdrawals.

Figure D2
Hartal effect among borrowers
Saving behavior



Notes: Graph in Fig. D2 reports, for the group of borrowers, the estimated coefficients of the *hartal* regression in Eq. (2) (precisely, the estimated coefficients displayed in Table 5bis). The two vertical lines delimitate the hartal event: "H1" indicate the first day of hartal; "H2" indicates hartal days that follow (and are consecutive to) the first one. Net savings is deposits minus withdrawals.

Figure D3
Hartal effect among borrowers
Borrowing behavior



Notes: Graph in Fig. D3 reports, for the group of borrowers, the estimated coefficients of the *hartal* regression in Eq. (2) (precisely, the estimated coefficients displayed in Table 6bis). The two vertical lines delimitate the hartal event: "H1" indicate the first day of hartal; "H2" indicates hartal days that follow (and are consecutive to) the first one. Net borrowing is loans taken minus repayments.