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Flexible Microfinance Products for Financial Management by the Poor: Evidence from SafeSave

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Well-functioning financial services are key for consumption smoothing and to take advantage of investment opportunities. Even though poor households badly need financial services for their day-to-day money management, a commonly held view is that they are 'too poor' to save and to repay loans with flexible terms. This paper explores whether this view holds true for two specific flexible financial products, namely passbook savings accounts and credit lines. Analyzing the daily transactions and balances in more than 10,000 SafeSave accounts—a microfinance institution based in Dhaka, Bangladesh—over nine years (2004-2012) shows that clients make extensive use of their flexible savingsand-loan-accounts to accommodate changing availability of and needs for liquidity in the face of three kinds of events: paydays, Islamic festivals (*Ramadan*, *Eid al-Fitr*, and *Eid al-Adha*), and political protests (*hartals*). Cash-in (savings deposit and loan repayment) flexibility is used to cope with both positive (paydays) and negative shocks (Islamic festivals and political protests); cash-out (withdrawal and loan taken) flexibility is used if the negative shock is anticipated well in advance (as in the case of Islamic festivals). We show that, while interest rates on loans are higher than in competing MFIs, repayment rates are comparably high. We also show that SafeSave is covering its operational costs, indicating that this type of flexible financial services can be offered to the poor in a sustainable fashion. Overall, analysis of the SafeSave experience shows that flexible financial products are much in demand by the poor and that they can be profitable for the microfinance institution that offers them.

Keywords: Bangladesh, liquidity, household finance, contract design.

JEL Classifications: D03, D14, G21, 012.

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Abstract

Well-functioning financial services are key for consumption smoothing and to take advantage of investment opportunities. Even though poor households badly need financial services for their day-to-day money management, a commonly held view is that they are 'too poor' to save and to repay loans with flexible terms. This paper explores whether this view holds true for two specific flexible financial products, namely passbook savings accounts and credit lines. Analyzing the daily transactions and balances in more than 10,000 SafeSave accounts—a microfinance institution based in Dhaka, Bangladesh—over nine years (2004-2012) shows that clients make extensive use of their flexible savings-and-loan accounts to accommodate changing availability of and needs for liquidity in the face of three kinds of events: paydays, Islamic festivals (*Ramadan, Eid al-Fitr*, and *Eid al-Adha*), and political protests (*hartals*). Cash-in (savings deposit and loan repayment) flexibility is used to cope with both positive (paydays) and negative shocks (Islamic festivals and political protests); cash-out (withdrawal and loan taken) flexibility is used if the negative shock is anticipated well in advance (as in the case of Islamic festivals). We show that, while interest rates on loans are higher than in competing MFIs, repayment rates are comparably high. We also show that SafeSave is covering its operational costs, indicating that this type of flexible financial services can be offered to the poor in a sustainable fashion. Overall, analysis of the SafeSave experience shows that flexible financial products are much in demand by the poor and that they can be profitable for the microfinance institution that offers them.

Keywords: Bangladesh, liquidity, household finance, contract design.

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1. Introduction

The lives of the poor are marked not only by low income, but also by highly variable income streams and frequent expenditure shocks. As a consequence, they need to actively manage their money to smooth out irregular income cash flows, cope with shocks such as health problems, or mobilize large sums of money for special occasions such as weddings and business opportunities. However, the financial instruments they use are largely informal, costly, and risky, making financial management inefficient (Collins *et al.*, 2009). In response to this situation, practitioners, policy makers, and researchers have shown interest in exploring which financial products may help the poor manage their money more efficiently.

Day-to-day cash-flow management is an important issue for poor households. As shown by Collins *et al.* (2009, p. 178), it consists in "manipulating small and irregular or unreliable incomes to ensure that cash is available when needed, so that there is food on the table every day, small but unpredictable needs like a visit to the doctor are met, and low-value but recurrent outlays, say for school fees or book, can be provided for. Managing money in this way absorbs a very large share of the time poor households give to financial affairs." Hence, understanding how formal financial products can fulfill this function is important for the development of appropriate financial institutions.

Flexibility in financial products has two sides. On the one hand, it is necessary to manage money on a day-to-day basis. It allows matching financial transactions such as savings deposits, loan repayments, withdrawals, and loan disbursements with clients' cash flows. Flexible financial products also allow households to keep liquidity management out of home (at the bank), where it is secure and possibly less subject to temptation spending and to money requests from family members (Dupas and Robinson, 2013; Bachas *et al.*, 2017). On the other hand, a commonly held view is that the poor are 'too poor' to effectively manage flexible products. Self-control problems coupled with stringent budget constraints lead them to under-save and/or over-borrow when using flexible products (Bertrand *et al.*, 2004; Bernheim *et al.*, 2015). This paper explores these competing views for two specific flexible financial products, namely passbook savings accounts and credit lines.

SafeSave, a microfinance institution (MFI), offers to Dhaka slum dwellers voluntary micro-savings and microcredit products designed to improve their financial management (Rutherford, 2011; http://www.safesave.org). Among SafeSave products, the savings-and-loan accounts have been qualified as the most flexible microfinance products in the world (Dehejia *et al.*, 2012; Labie *et al.*, 2017). In these accounts, clients can deposit and withdraw money at any time for any amount (as in liquid bank accounts), and loans are repaid freely with no maturity or fixed installments (as in credit lines). Our dataset consists in the 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 examine the individual client time paths of deposits, withdrawals, loans taken, and loan repayments in relation to three sources of shocks affecting availability of and need for liquidity. First, we observe responses to paydays, contrasting individuals with irregular jobs (with weekly income) and individuals with regular jobs (with monthly income). Second, we analyze the response to Islamic festivals, namely *Ramadan* (Muslim holy month of fasting), *Eid al-Fitr* (that marks the end of *Ramadan*), and *Eid al-Adha* (the sacrifice feast), which all induce increases in expenditures and, for the case of *Ramadan,* a decline in income/productivity (Schofield, 2014). Third, we look at political protests (called *hartals* in many south Asian languages), which are general strikes involving a total shutdown of schools and places of business. *Hartals* can imply significant income losses for the poor, especially if the protests last for two or more consecutive days (Chawdhury, 2000; UNDP, 2005; Ashraf *et al.*, 2015). All three shocks are anticipated: paydays and Islamic festivals are recurrent/seasonal shocks, and *hartals* are sporadic shocks, typically announced a few days in advance. Focusing on these anticipated events, we analyze individual clients' financial strategies, which include both ex-ante and ex-post adjustments.

We run fixed-effect (FE) panel regressions, which include individual FEs, seasonal FEs, and a trend. The individual FEs control for unobserved time-invariant individual characteristics. The quadratic trend results in stationary time-series. The different seasonal FEs characterize both Gregorian and Islamic calendars. They are particularly interesting for our analysis as they capture the effect of recurrent shocks: day-of-the-Islamic-week FEs capture the weekly payday effect; week-of-the-Gregorian-month FEs capture the monthly payday effect; and the week-of-Islamic-year FEs capture the Islamic festival effect. Finally, to capture the *hartal* effect on saving and borrowing, our regression models include *hartal* dummies indicating the days before *hartals,* the *hartal* days, and the days after *hartals*.

Regression results show that the poor do make extensive use of the flexible savings-and-loan accounts offered by SafeSave in the face of these events. We find that the cash-ins into SafeSave accounts—that is, the sum of savings deposits and loan repayments—are the highest right after paydays, specifically on Saturdays and on the second week of the Gregorian months. This result suggests that SafeSave clients save and repay loans as soon as they receive income; they do not spend all the income received, but partly put it aside to save and repay loans; and they do so spontaneously, even if not obliged by a compulsory deposit or loan repayment schedule.

Second, we look at the week-of-Islamic-year FEs. Our regressions show that savings balances (outstanding loan balances) progressively increase (decrease) in the first 33 weeks of the Islamic year, and drop (peak) between weeks 34th to 39th, which correspond to *Ramadan* and *Eid al-Fitr*. Similar effects (same sign but smaller in magnitude) occur before and during *Eid al-Adha*. Overall, these results indicate that clients spontaneously and strategically store liquidity before festivals, building savings and repaying loans, and that they dis-save and borrow during festivals.

Third, controlling for a quadratic trend, seasonality, and individual FEs, we look at the coefficient estimates of the three types of *hartal* dummies, indicating respectively pre-*hartal*, *hartal*, and post-*hartal* days. Cash-ins are significantly higher in the pre-*hartal* days and on the first *hartal* day. This result indicates that clients increase their savings in anticipation of the income loss due to the *hartal.* Cash-ins are significantly lower on the second and consecutive *hartal* days and on the first post- *hartal* day*,* when the income loss possibly occurs. Finally, cash-ins are significantly higher on the second post-*hartal* day when income recovers.

Overall, the analysis of SafeSave clients' use of their accounts shows that they make extensive use of the flexibility features offered by SafeSave: flexible loan duration periods, flexible time intervals between consecutive installments, flexible initial grace periods in loan repayment, and flexible timing of interest payments relative to due date. We show that SafeSave clients save up (accumulate savings and repay loans) during positive shocks (paydays) and/or in anticipation of negative shocks (Islamic festivals and *hartals*). They save down (dis-save and borrow) when negative shocks (Islamic festivals) occur. Cash-in flexibility is used to cope with both positive (paydays) and negative shocks (Islamic festivals and political protests); cash-out flexibility is used only if the negative shock is anticipated well in advance (as in the case of Islamic festivals). The results are robust across various econometric specifications, which we run both at the aggregate (branch) level and at the individual level.

Subsequently, we investigate the comparative performance of SafeSave as a financial institution. While the interest rate on loans is higher than in competing Bangladeshi MFIs (particularly BRAC, Grameen Bank, and ASA), repayment rates have been comparably high. Importantly, SafeSave is covering its operational costs, showing that flexible financial services can be offered to the poor in a sustainable fashion by a non-profit institution.

The remainder of the paper is organized as follows. Section 2 presents the related literature. Section 3 describes the SafeSave dataset. Section 4 presents general evidence on the use of flexibility. Section 5 describes how flexibility is used in response to shocks. In section 6, we examine the repayment performance of SafeSave and its profit and loss accounts. Section 7 concludes.

2. Related Literature

Our paper relates to the discussion on the role of regular and frequent repayment rules common to most microfinance credit operations. The main argument in favor of strict repayment rules is the discipline that they impose on borrowers, preventing delinquency on loans. However, frequent repayments often mismatch with the poor's irregular income flows and hence can be difficult to respect and may constrain the use of loans for productive investment. Empirical studies addressing this issue have mostly looked at two ways of making typical microfinance credit contracts more flexible: either reducing the frequency of payments (from weekly to bi-weekly or monthly) or providing a grace period. Results on providing this limited flexibility are mostly but not exclusively positive. Reducing the frequency of repayments is found to either have no negative effect on repayment (Field and Pande, 2008; Shonchoy and Kurosaki, 2014), or to decrease the default rate (McIntosh, 2008). Field *et al.* (2012) found that it further reduces financial stress and induces higher business income and investment. A variation on the subject is a contract in which the repayment schedule remains rigid but is tailored to the borrower's specific income profile (Czura, 2015; Weber and Musshoff, 2013). Granting a temporary moratorium during the lean season is shown to have no negative effect on repayment by Shonchoy and Kurosaki (2014), while Field *et al.* (2013) show an increase in default rates by small entrepreneurs offered a contract with a two-month grace period before the start of repayment. Field *et al.* (2013) however also find that the grace period increased short-run business investments and long-run profits. An experiment with a more flexible grace period is reported in Barboni and Agarwal (2017). Microfinance borrowers were offered the choice of a standard rigid contract or of a more expensive flexible contract that gave them the opportunity of exercising a three-month repayment holiday, twice over the entire loan maturity of two years, at the time of their choice. A control group was only offered the standard contract. They found that the treatment induced higher repayment rates as well as higher business sales, with an important mechanism being the selection by which the most time-consistent and financially disciplined clients chose to take the flexible loan. In a similar lab-in-the-field game, Barboni (2017) found that the most entrepreneurial and less risk-averse entrepreneurs chose the flexible contracts.

Our paper also relates to the benefits of access to formal savings products, which allows people to put their money away from home, addressing the issue of safety and reducing problems of self-control and demand from others that can constrain their savings. Access to formal savings instruments has been shown to decrease short-term debt and protect consumption against economic shocks (Kast and Pomeranz, 2014), increase agricultural inputs, output, and household consumption (Brune *et al.*, 2015), and increase individuals' willingness to take risks (Carvalho *et al.*, 2016). However, while access to savings in itself has recognized large benefits, savings behavior is subject to behavioral constraints. Problems of self-control, temptation goods, or inattention all lead people to save less than they would want to save. A large literature thus addresses the role of *commitment in savings*, with commitment sought on either the deposit or the withdrawal side. On the deposit side, use of a default option for either automatic deposits (hard commitment illustrated in Duflo *et al.*, 2006) or suggested deposits (soft commitment, as in Atkinson *et al.*, 2013) shows a very clear increase in savings. On the withdrawal side, commitment savings accounts typically disallow withdrawals until a set date or a set amount has been accumulated, or for a pre-specified purpose. The trade-off here is again between discipline that can help accumulate savings and reach one's own plan, and rigidity that prevents the withdrawing of one's own resources in case of unexpected shock or opportunity. A soft commitment version on the withdrawal side consists in labeling the account for a pre-specified type of expenditures (Karlan and Linden, 2014, for education; Dupas and Robinson, 2013, for health). Results from these experiments show that commitments are more attractive to those with strong demands from their social networks (Dupas and Robinson, 2013) and for those with low discount rates or time inconsistency (Ashraf *et al.*, 2006). Results in general show that commitment leads to higher saving balances, but that most of the benefits come with the soft commitment or labeling of the savings account, rather than the hard commitment. Dupas and Robinson (2013) also show the interesting result that hard commitment is only effective when dedicated to emergency rather than to preventative health expenses.

While credit and savings called on different instruments and hence are experimented separately, one should be clear that they both serve the same purpose of reconciling flows of income and flows of expenditures, and hence ought to be highly substitutable. The starting point with these two instruments is however quite different. Microcredit is in general very rigid, and has gradually been experimenting with some limited forms of flexibility. But none of these experiments proposes what would be a fully flexible product such as, for example, a credit line with no maturity date and no fixed repayment schedule. Savings are in general completely flexible, all the way to the inalienable possibility of saving on one's own at home, and recent experiments are looking at the benefits of introducing commitments. For that reason, microfinance credit can also be considered as a form of saving commitment, which offers the discipline of loan repayment when saving is harder to commit to (Collins *et al.*, 2009; Morduch, 2010; Bauer *et al.*, 2012; Afzal *et al.*, 2017). In this paper, we look at a product that offers full flexibility both for credit and for savings: it is the combination of credit with no maturity date and no fixed repayment schedule, and of passbook savings with discretionary deposits and withdrawals.

The existing literature uses randomized control trials (RCT) and restricts attention to the impact of flexible products on various individual behaviors such as consumption smoothing, risk-taking, savings accumulation, and loan repayment. This paper aims at complementing this burgeoning RCT literature on the impact of microfinance, thanks to a unique panel database on the clients of SafeSave. While the nature of our dataset does not allow straightforward causal inference, its richness and time coverage permit observation of the long-run evolution of saving and borrowing behavior at the individual level. This allows us, for the first time in the literature, to look at how poor households use fully flexible savings and credit products in real-life and for an extended period of time.

Our paper also fits into a line of studies examining risk-coping mechanisms in developing countries. Shocks are a major source of vulnerability to poverty (Townsend, 1995; Udry, 1995). They may even affect personal characteristics such as attitude toward risk and impatience, which have been shown to contribute to the reproduction of poverty (Gloede *et al.*, 2015; Cassar *et al.*, 2017). Mechanisms to cope with shocks are in high demand among the poor (Lee and Sawada, 2010). Unfortunately, with the instruments available to them, they are barely able to hedge against shocks (Collins *et al.*, 2009). They have limited access to formal insurance (Platteau *et al.*, 2017). Their use of social networks for insurance is psychologically and practically costly (Baland *et al.*, 2011) and it proves to be inefficient under common shocks (Townsend, 1994). Microfinance loans are typically too rigid and, hence, cannot be used for hedging against shocks (Ambrosium and Cuecuecha, 2016).

For consumption smoothing, poor households extensively use informal borrowing (from money lenders) and the depletion of productive assets such as stored grain and livestock (Paxton and Young, 2011). However, this can have detrimental effects on future consumption (Fafchamps *et al.*, 1998; Khan *et al.*, 2015). Experimental evidence shows that liquid bank accounts improve resilience to small income shocks by poor households (Kast and Pomeranz, 2014; Prina, 2015). However, real-life evidence suggests that the poor cannot afford to hold unproductive sufficient levels of`` liquid assets for consumption smoothing (Jalan and Ravallion, 2001; Laureti, 2017). Our paper, by looking closely to the demand and supply of fully flexible products, indirectly explores whether these products may effectively work as a risk-coping mechanism.

3. Data

We use a unique database released by SafeSave. 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 US$ 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 (US$ 63) per borrower.

SafeSave products offer a combination of flexibility and behavioral discipline. They consist in: i) passbook savings accounts with daily home visits of collectors; ii) loans with flexible repayment schedules limited to only one outstanding loan at a time and where collateral is provided by a required saving balance of one-third of outstanding loans; and iii) long-term savings accounts with fixed maturity, regular monthly deposits, and finite penalty for early withdrawals.

This paper focuses on the first two SafeSave products, henceforth referred to as savings-and-loan accounts. They are fully liquid no-maturity accounts. Deposits and withdrawals can be made at any time (except on Fridays, when SafeSave is closed) and for any amount. Deposit collectors visit each client daily at their home or workplace. This practice encourages deposits and also makes savings accounts immediately accessible. SafeSave's active clients (i.e., who hold a flexible savings account) are also allowed to borrow. Loans are repaid freely, with no maturity or fixed installments. The only compulsory payments are the monthly interests. As of August 2012, clients pay a 30% yearly interest on outstanding debt and earn a 6% annual interest on savings balances. The maximum loan amount increases with good repayment history; importantly, the loan amount can never exceed three times the outstanding savings balance. Clients can access a new loan only after the previous one has been fully repaid. Finally, SafeSave allows only one loan per household and only 16-year or older clients can borrow. We use these two latter restrictions to determine the group of *potential* borrowers, i.e., SafeSave clients who are allowed to borrow.

The unbalanced panel dataset includes 12,647,376 day-client observations, concerning 10,631 clients for the period from January 2004 to August 2012. We focus on four SafeSave branches (Gonoktuli, Kurmitola, Millat, and Muslim) that offered the exact same saving and credit opportunities during the observation period.[1] From the original dataset made of 16,071 clients, we selected the 12,244 *potential* borrowers, i.e., clients who are allowed to borrow according to SafeSave rules. Because of the presence of some highly influential observations (outliers), we remove the 1,613 individuals with extreme values of transactions and/or balances (specifically, we exclude clients with the 5% highest transactions—i.e., saving deposits, withdrawals, loan repayments, and loans—and with the 5% highest savings balances and outstanding loan balances).[2] We observe daily transactions in the savings-and-loan accounts. From daily transactions, we compute daily savings balances and outstanding loan balances. Beside financial variables, we observe a few client characteristics, including gender, age, duration of the relationship with SafeSave, and professional occupation.

[1] SafeSave was created in 1996, but out of the four branches that we analyze, three were opened after 2004. The fourth (Kurmitola) was launched before 2004, so that at least some clients from that branch were already active with SafeSave before 2004.

[2] Outliers are particularly relevant in savings. Daily savings deposits in the top 5% tail of the distribution are between BDT 4,000 (USD 50) and BDT 1,300,000 (USD 16,250). Many of these deposits—especially the very large ones—are transitory; they are followed immediately by a withdrawal of the same amount. To be safe, we excluded the top 5% tail of the distributions of transactions and balances. For robustness, we perform the analysis with the 1% outlier threshold (Appendix 1).

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 individuals allowed to borrow, i.e., they are at least 16 years old and belong to non-borrowing households.

< Table 1 here >

The majority (85%) of clients are women. 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 the self-employed (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% are "regular" workers with a job in the formal sector. They earn a regular, fixed wage, typically paid on a monthly basis. The vast majority (72%) of formal sector workers are garment factory workers. The rest are guards at schools or hotels, teachers, medical staff of hospitals, or home servants. "No occupation" includes mostly housewives (95%); the rest are students (4%), unemployed, and retired people.

To describe the financial transactions of SafeSave clients, it is useful to compare their size to the average wage. During the 2004-12 period, the average monthly wage in Bangladesh was BDT 4,517 (US$ 56). It increased from BDT 3,111 (US$ 39) in 2004 to BDT 6,469 (US$ 81) in 2012. On the savings side, SafeSave clients save-up small amounts of money—on average BDT 45 (US$ 0.6, equivalent to 1% of the average monthly income)—every week and withdraw about BDT 724 (US$ 9, 16% of monthly income) every seven months.[3] Non-borrowers on average make more deposits and withdrawals than borrowers, but of slightly lower amounts. In our sample, clients hold BDT 1,253 (US$ 16, 29% of monthly income) in their savings accounts, on average. Non-borrowers hold lower savings balances than borrowers, respectively BDT 603 (US$ 8, 14% of monthly income) and BDT 1,447 (US$ 18, 32% of monthly income). However, given the one-third rule for compulsory savings, borrowers' liquid savings balances amounting to BDT 575 (US$ 7, 13% of monthly income) are on average not significantly different from non-borrowers' liquid savings. As Table 1 shows, the size of monthly deposits is slightly higher than the size of monthly withdrawals, hence during the observation period clients accumulated

[3] 1 US dollar (USD) is equivalent to about 80 Bangladeshi takas (BDT) in the study period.

savings. The growth rates of aggregate liquid savings balances are 18% and 16% per year among non-borrowers and borrowers, respectively. The average inflation rate over the observation period was 7.9%.[4]

On the borrowing side, 8,184 clients borrowed on average BDT 4,450 (US$ 56, 100% of monthly income) every 19 months. 62% of them took two or more loans, with loan size (initial amount) between two successive loans increasing on average by 37%. They make on average two repayments per month, with a relatively small average installment of BDT 236 (US$ 3, 5% of monthly income). The average outstanding loan among borrowers is BDT 2,616 (US$ 33, 59% of monthly in come).

4. Evidence on the use of flexibility

The loans offered by SafeSave offer three dimensions of flexibility that are in sharp contrast with standard MFI loans: loan maturity, frequency of repayments, and flexibility of 30 days for the interest payments. Before further analysis, we document here that clients do use this flexibility.

Considering the 14,393 completed loans in our observation period, the average time to full repayment is 12 months. This is not different from the standard year-long loan of most MFIs, but as seen in Figure 1, there is very large heterogeneity in loan duration, spreading from one month to more than three years. 37% are repaid within six months, 72% within one year, 89% within two years, and 5% of the loans last for more than three years. And there is no evidence of a modal point at one year.

< Figure 1 here >

The schedule of repayments is also completely flexible. With collectors coming by every day, borrowers can repay as frequently as they want, with no additional transaction costs, and in amounts that they want. But there is no obligation of any minimum frequency. Panel A of figure 2 reports the distribution of time between loan disbursement and first installment, that is, the initial grace period. The distribution is very bimodal, with 43% made within seven days from disbursement, 15% more than a month after, and 5% more than two months after. Panel B of figure 2 shows the distribution of time between two consecutive loan payments (excluding the initial grace period). This is again very bimodal. More than 30% take place the day following the previous payment. The median is two days after, and 7% of these time periods are longer than 30 days. These two graphs show that there is a demand for long grace periods, either at the beginning of the loan, or later into the repayment of the loans. At the same time, borrowers seem to make payments at a very high frequency. Loans are expensive to hold, transaction cost for repaying any small amount null, and hence this seems to be a very rational behavior.

[4] http://data.worldbank.org (retrieved on February 8, 2017).

< Figure 2 here >

While loans can be repaid at any time, SafeSave prescribes clients to pay regular monthly interests within 30 days from the due date. We ask whether clients use this '30-day flexibility' in loan interest payments. Figure 3 reports the number of days between due date and payment dates for the interest payments (207,108 in total) that we observe. Note that the great majority (94%) are paid within 30 days, the maximum delay allowed by SafeSave; 3% are paid with only one day of delay, and the remaining 3% are paid with two or more days of delay. While there is a large concentration of payments in the 28-30 days window, a large fraction (62%) is paid before that time.

< Figure 3 here >

The patterns that we observe speak to the innovations that many MFIs are currently introducing to add some flexibility to their standard rigid loans. Like Barboni and Agarwal (2017), we observe the demand for grace periods. On the other hand, we do not see an obvious demand for a lower frequency of payments. Anticipating the questions related to defaults and payment performance that we will address in section 6, the flexibility given to and used by Safe Save clients is not associated with worse performance than observed in other MFIs.

5. Use of flexibility in response to shocks

We now turn to a detailed examination of individual client's time paths of deposits, withdrawals, loans taken, and loan repayments to show how this flexibility is used in relation to irregularities in availability of and need for liquidity. Specifically, we consider three common and anticipated shocks: paydays, Islamic festivals, and political protests.

Paydays, i.e., the days when individuals receive their wage, are positive liquidity shocks that occur recurrently with a weekly or monthly frequency depending on the occupational category. Irregular workers are typically paid weekly, on Thursday, the last working day of the Islamic week. By contrast, regular workers, in this case mostly garment factory workers, are paid monthly, normally during the first week of the following (Gregorian) month.[5]

Islamic festivals (namely, *Ramadan*, *Eid al-Fitr*, and *Eid al-Adha*) are negative liquidity shocks for two reasons. One is that individuals are particularly keen to spend during Islamic festivals; the other is that during *Ramadan* (the Islamic holy month of fasting) income declines because productivity is on

[5] https://www.hrw.org/report/2015/04/22/whoever-raises-their-head-suffers-most/workers-rights-bangladeshs-garment (retrieved on December 10, 2017).

average lower (Schofield, 2014). As with paydays, Islamic festivals are recurrent shocks: *Ramadan* and *Eid al-Fitr* (which marks the end of *Ramadan*) happen between the 34th and 39th weeks of the Islamic year; *Eid al-Adha* occurs toward the end the Islamic year, around the 48th and 49th weeks.

Political protests, called *hartals*, create negative liquidity shocks. *Hartals* are mass protests or general strikes involving the total shutdown of workplaces, offices, and shops as a form of civil disobedience. They are often used for political reasons, for example by an opposition political party protesting against a government policy or action. They are common in Bangladesh and typically intensify as the country approaches elections. They have been shown to have significant economic costs, such as absence of work for daily earners, disruptions in transport system leading to shortages in food supply, higher prices, and defaults in loans due to a slump in business activity (Ashsan and Iqbal, 2014; Ashraf *et al.*, 2015). Globally, *hartals* produce an important income loss for the poor, especially when they last for two or more consecutive days (Chawdhury, 2000; UNDP, 2005).

As data on *hartals* are not readily available, we retrieved information from the Daily Star, the most popular English language daily newspaper in Bangladesh. This information is crosschecked with the dataset used by Shonchoy and Tsubota (2015). For each *hartal*, we know the announcement date and the occurrence date. *Hartals* can be as short as two hours or may last for multiple days (up to six days). We identify as 'severe' *hartals* that last more than 24 hours. During the 2004-2012 study period, we observe 45 short *hartals* of less than 24 hours and 18 severe *hartals* that lasted on average three days. In contrast to paydays and Islamic festivals that are recurrent shocks known well in advance, *hartals* are sporadic shocks and typically announced only a few days in advance, in our sample on average 5.5 days.

5.1 *Estimating equations*

We estimate panel regressions for the years 2004 to 2012, with individual FEs, different time (seasonality) FEs, and a time trend:

$$Y_{itdwx} = \alpha_d + \beta_w + \gamma_x + T(t) + \mu H1_t + \pi H2_t + \sigma PreH_t + \sum_d \rho_d PostH_{d,t} + u_i + \varepsilon_{itdwx} \quad (1)$$

where Y_{itdwx} is an outcome variable for individual *i* at time (day) *t*. Outcome of interest are individual daily balances (savings balances, outstanding loan balances) and transactions (savings deposits, withdrawals from savings, loans taken, and loan repayments).

The terms $\alpha_d, \beta_w, \gamma_x$ represent different time FEs: α_d represents the days of the week FEs (from Saturday to Friday); β_w the weeks of the month FEs according to the Gregorian calendar (from week 1 to 5); and γ_x indicates the weeks of the year FEs according to the Islamic calendar (from week 1 to 51).

Among regressors, we include various *hartal* dummies. We expect *hartals* to affect saving and borrowing: on the same day (simultaneous effect), on the preceding days (anticipation effect), and on the following days (recovery effect) (Ashraf *et al.*, 2015). The simultaneous effect should be larger for severe *hartals*. Therefore, we define six binary indicator variables: (i) $H1_t$ takes the value of one for the first *hartal* days and zero otherwise; (ii) $H2_t$ takes the value of one for the second, third, fourth, and so on, consecutive *hartal* days, and zero otherwise; (iii) $PreH_t$ is a dummy variable indicating the period from the announcement to the on-start of the *hartal*; (iv) $PostH_{d,t}$ are three indicator variables for the d^{th} days after the *hartal*, where $d = 1, 2, 3$.

$T(t)$ is a quadratic trend to control for the potential problem of non-stationarity of the time series. Given that we have an unbalanced panel, Baltagi (2005) suggests to run a Fisher-type test based on augmented Dickey-Fuller test for unit root. We also run an Im-Pesaran-Shin unit-root test, which is feasible with unbalanced panel datasets. Both tests conclude that flow variables (i.e., savings deposits, loan repayments, withdrawals, and loans taken) do not contain unit roots, i.e., that they are stationary. In contrast, stock variables (savings balances and outstanding loan balances) are non-stationary. Since the quadratic trend is significant, we control for it and we verify the stationarity of the residuals.

Finally, we perform a Hausman test to examine whether we should apply a FE or a random-effect model for Eq. (1). With p-values of 0.0000, we can reject the null hypothesis that a random-effect specification should be preferred. Hence, the term u_i controls for individual time-invariant characteristics and ε_{itdwx} is the error term.

In the following sections, we report the results of the estimated Eq. (1) for the various outcomes of interest *Y*, discussing in turns the estimated coefficients related to paydays (α_d and β_w), those related to Islamic festivals (γ_x), and then to *hartals* (μ, π, σ, and ρ_d).

5.2 *Payday effects*

Figure 4 represents the estimated day-of-week FEs α_d, starting with Saturday, the first day in the Islamic calendar. It shows that cash-ins (savings deposits and loan repayments) are concentrated on the first day (Panel A). This reflects the income profile of irregular workers who are typically paid weekly, on Thursdays, the last working day of the Islamic week. With SafeSave being closed on Fridays, clients appear to be making their savings deposits and loan repayments right after payday. In contrast, the cash-outs (loans taken and withdrawals) are relatively low on Saturdays because SafeSave discourages its clients from taking loans on that day (Panel B).

< Figure 4 here >

Figure 5, reporting the week-of-Gregorian-month FEs (the estimated β_w), shows that cash-ins are concentrated in the second week (Panel A). This reflects the income profile of regular workers, who receive monthly pay on the first week of the following Gregorian month. Here again individuals seem to be saving right after paydays. Cash-outs are concentrated in the second week of the month because SafeSave clients can take a new loan only when they have finished to repay the previous one (Panel B).

< Figure 5 here >

5.3 *Islamic festival effects*

Figure 6 plots the week-of-Islamic-year FEs (the estimated γ_x). It shows that savings balances increase (and outstanding loan balances decrease) from the first to the 33rd week, which is the period before *Ramadan* and *Eid al-Fitr*. By contrast, savings balances drop (and outstanding loan balances increase) during *Ramadan* and *Eid al-Fitr*, in the 34th to 39th weeks of the Islamic year. A similar (but smaller in magnitude) pattern of saving and borrowing accompanies *Eid al-Adha*, which occurs in the 48th week. SafeSave clients clearly save up (save/repay loan) before festivals, and save down (dis-save/borrow) during festivals.

< Figure 6 here >

5.4 *Hartal effects*

We now turn to *hartals*. Tables 2, 3, and 4 display estimated coefficients associated with the *hartal* dummies for pre-*hartal*, *hartal*, and post-*hartal* days. Table 2 reports the *hartal* effect on savings accounts, looking at daily deposits, daily withdrawals, and daily liquid savings balances. Overall, a *hartal* seems to significantly affect savings deposits, but not withdrawals and savings balances.

< Table 2 here >

For savings deposits (column (1) of Table 2), the estimated coefficients for the ‘preparation period’ dummy and the $H1$ dummy are positive and significant. Point estimates suggest that SafeSave clients make BDT 0.3 (p <1%) higher savings deposits in the pre-*hartal* days (starting from the announcement day) and BDT 0.4 (p <1%) higher savings deposits on the first *hartal* day (mean value of savings deposits is BDT 4.0). During these days, clients possibly save more in anticipation of the income loss caused by the *hartal*.

In line with this interpretation, estimated coefficients are negative for the $H2$ dummy and ‘first day after *hartal*’ dummy (but statistically significant only for the latter dummy). Point estimates suggest that SafeSave clients make BDT 0.3 lower savings deposits on second and subsequent days of severe *hartals*, as well as on the first post-*hartal* day. In those days, savings balances (column (3) of Table 2) are also significantly lower by BDT 0.8 and 1.0, in line with the idea that clients save less when the income loss due to the *hartal* materializes. Finally, savings deposits are significantly higher by BDT 0.3 (p<5%) on the second post-*hartal* day, that is, when clients recover from the *hartal*. On the same day, withdrawals (column (2) of Table 2) are also significantly lower by BDT 0.5 (p <5%).

Table 3 reports the *hartal* effect on loan accounts for the subset of borrowers. We observe daily repayments, loans taken, and outstanding loan balances. In line with the savings deposits response described in Table 2, *hartal*s have a statistically significant effect on loan repayment (column (1) of Table 3), but not on loans taken and on balances. Clients make BDT 0.6 higher loan repayments on the first *hartal* day, and BDT 0.6 lower repayments on the second and consecutive *hartal* days.

< Table 3 here >

To confirm estimates in Tables 2 and 3, Table 4 displays the *hartal* effect on aggregate cash-ins and cash-outs. For cash-ins (column (1) of Table 4), results are in line with those outlined in columns (1) of Tables 2 and 3. The estimated coefficients of the 'preparation period' dummy and the 'H1' dummy are positive and significant. Point estimates suggest that SafeSave clients make higher cash-ins on the pre-*hartal* days and on the first *hartal* day, with coefficients of BDT 0.3 (p<1%) and BDT 0.6 (p<10%) (mean value of cash-ins: BDT 11.3). The estimated coefficients of the 'H2' dummy and of the 'one day after *hartal*' dummy are negative and significant (p<10%). Here, point estimates suggest that SafeSave clients make BDT 0.8 lower cash-ins on the second and subsequent *hartal* days, as well as on the first post-*hartal* day. The coefficient on the second post-*hartal* day is positive but not significant. For the cash-outs (column (2) of Table 4), estimated coefficients are not statistically significant. This confirms previous estimates of savings deposits and loan repayments reported in columns (2) of Tables 2 and 3, respectively.

< Table 4 here >

The contrast between the responses of SafeSave clients to the two negative shocks (*hartal* days and Islamic festivals) is worth noticing. During *hartal* days, they save up (accumulate savings and repay loans) significantly less than in regular days. However, they do not save down (withdraw and borrow) significantly more. In contrast, during Islamic festivities, clients save down significantly more than in other periods. The reason could be that Islamic festivals are anticipated a long time in advance, allowing clients to prepare for the festivities by accumulating liquidity that they can later draw down. Evidently, clients are not able to accumulate substantial liquidity when negative shocks are announced only a few days in advance (such as in the case of *hartals*). In a product design perspective, this analysis reveals that cash-ins flexibility is valuable to cope with sporadic shocks which are unanticipated or anticipated with little time in advance (for example, medical expenses). In contrast, cash-out flexibility is useful to cope with recurrent shocks and, more generally, shocks that are known with long anticipation (such as school expenses, festivities, and so on).

We perform in Appendix 1 some robustness checks for the results with respect to sample definition and functional forms. Specifically, we rerun the analysis cutting only the extreme outliers (1% extreme transactions, rather than 5%), and including all the clients of SafeSave, rather than only the potential borrowers, and find very similar results. We also experiment with alternative time trend functional forms (linear and log-linear). These specifications do not correct for the non-stationarity of the time series. Finally, we perform the analysis at the branch level, using the average per-client transactions and balances. Results are very similar, although somewhat less precise for hartal effects.

6. SafeSave performance

In this section, we take an institutional perspective. Flexible financial services can be tremendously costly for the institutions delivering them for two main reasons. First, flexibility in loan repayment may increase default rates (Field *et al.*, 2013). Second, flexibility may increase operational costs (Jeon and Menicucci, 2011). To check this, we compare loan repayments and interest rates charged by SafeSave with those of competing MFIs offering standard rigid loans. We also report figures on SafeSave's profit and loss statement.

6.1 *Loan repayment and interest rate*

The MFIs to which we compare SafeSave are ASA, BRAC, Grameen Bank, and BURO, the four largest MFIs operating in Bangladesh.[6] These MFIs all offer rigid loans, with fixed repayments schedule and fixed maturity. Standard performance indicators are based on timely repayment of principals. Since there is full flexibility on the timing of repayment of outstanding loans with SafeSave, no such indicators can be calculated. Instead, we compute similar performance indicators based on timely payment of interests.

We analyze loan repayment performance using four indicators commonly used by the microfinance industry (Rosenberg, 2009): (i) loans at risk, (ii) portfolio at risk, (iii) write-off ratio, and (iv) loan recovery rate. Results are reported in Table 5, Panel A for SafeSave and Panel B for the four comparison MFIs.

< Table 5 here >

"Loans at risk—LAR (X days)" is the number of loans more than X days late divided by the total number of outstanding loans. For each loan, we compute the average number of days used to repay the

[6] Information on these four MFIs is retrieved from the web.

interests. Globally, 1,110 loans (6% of total) have interest payments on average more than one day late; 544 have interest payments more than seven days late and 136 (0.74%) more than 30 days late. Unfortunately, information on LAR is not available for the four comparative MFIs.

"Portfolio at risk—PAR (X days)" is the outstanding principal balance of all loans past due more than X days divided by the outstanding principal balance of all loans. We compute the value of interests past due more than X days divided by the total value of interest due. For example, interest payments past due more than one day are BDT 3,539,881, corresponding to 12.6% of total interest payments (BDT 28,183,728). Interest payments past due more than 7 days are BDT 1,433,541 (5.1%) and more than 30 days BDT 1,083,743 (3.8%). The PAR(30) at SafeSave (3.8%) is in line with the PAR(30) at the four comparative MFIs, which have a PAR(30) between 0.99% and 10.66%

The "write-off ratio" is the value of loans written off during a period divided by the average gross loan portfolio during the same period. At SafeSave, the total value of loans written-off is BDT 623,856, corresponding to 0.70% of total loaned amount (BDT 88,526,200) during the study period. The write-off ratio of the four comparative MFIs ranges between 0.00% and 1.84%.

The "current recovery rate" (CRR) is the cash collected during the period from borrowers divided by the cash falling due for the first time during the period under the terms of the original loan contract. For SafeSave clients, we compute the CRR as the amount of interest paid over the amount of interest due (equivalent to the sum of interest paid and the interest remaining unpaid for 30 days or more). During the observation period, CCR of interest payments is 96.2% (BDT 26,242,579 interests paid over BDT 27,284,562 total interests due for more than 30 days). This is slightly lower than the 96.9-98.2% CRR of the four comparative MFIs.

In conclusion, this analysis shows that SafeSave borrowers make interest payments on their loans with the same discipline as borrowers from other MFIs with fixed repayment schedules.

While the repayment rates of flexible and rigid loans are similar, the interest rates charged on flexible loans are higher than those on rigid loans. Specifically, SafeSave charges a 30-36% interest rate per year, compared to rates of 20% to 27% by the comparative MFIs. The higher interest rate at SafeSave reflects the higher operational costs that it has to incur for the flexible features of its products, for example in employing payment collectors. However, according to estimates given by SafeSave, approximately 35% of its borrowers are also clients of other MFIs. This willingness to pay higher rates is thus a measure of the value these clients attribute to the flexibility the SafeSave loans have relative to the rigid scheme offered by the competing MFIs. This is in line with what Barboni (2017) and Barboni and Agarwal (2017) find in India.

6.2 *Profits and losses*

Figure 7 shows the composition of revenues and costs of SafeSave for the years 2004-2012. Revenues (Panel A) come mainly from the interests on loans paid by borrowers: interest earnings generated 92% of total SafeSave revenues in 2004; the share progressively decreased every year, until it reached 70% of total revenues in 2012. The second important source of revenues is the interest payments that SafeSave receives from a bank on its cash reserves: it constitutes 3% of revenues in 2004 and progressively increases to reach 25% of total revenues in 2012. Finally, headquarter income—a fixed fee that the nine SafeSave branches have to pay to headquarter—generated between 5% and 7% of SafeSave revenues in the observation period.

<Figure 7 here>

The most important costs (Panel B) are operational such as staff salaries and management provisions. They absorbed 81% of total revenues in 2004. This share progressively declined to 54% of total revenues in 2012. The second important source of costs is interests paid to savers: this cost absorbed only 7% of SafeSave revenues in 2004, rising to 16% of total revenues by 2012. A turning point was 2010 when SafeSave started offering long-term savings account.

Finally, SafeSave has been profitable since 2004. Its profit margin was 2% of revenues in 2004 and it peaked at 16% in 2012.

7. Conclusion

This paper explores whether flexible financial products can be effective to help poor households manage their cash-flows. To do this, we exploit a unique dataset released by SafeSave, an MFI offering flexible savings-and-loan accounts to poor households in Dhaka, which is likely the most salient example of fully flexible microfinance products in the world. Our dataset informs the daily financial movements in the savings-and-loan accounts of 10,631 SafeSave clients for the period stretching from January 2004 to August 2012.

We examine the responses of SafeSave clients to three sources of irregularities in their availability of and need for liquidity: regular paydays, periodic Islamic festivals, and political protests. Results show that the poor do make extensive use of the flexible savings and credit products offered by SafeSave to accommodate their changing availability of and needs for liquidity in the face of these three events. Our study provides the first empirical evidence of use by a very poor population of fully flexible savings-and-loan accounts. We also compare repayment rates observed at SafeSave with those of high performing

MFIs in Bangladesh such as BRAC and the Grameen Bank. We show that the poor manage to repay their loans on time even when they are not forced to do so with a fixed and rigid repayment schedule.

In contrast to the general opinion in microfinance, these results show that poor people are able to save and repay loans based on their own decisions, without the constraint of a fixed payment schedule. Our findings are in line with the literature showing that flexible loan repayment schedules do not increase clients' defaults. In fact, flexible features and behavioral discipline can coexist in microfinance products (Labie *et al*., 2017). Importantly, SafeSave data on costs and revenues indicate that flexible micro-savings and microcredit products can be provided in a sustainable fashion by non-profit institutions. These results should encourage microfinance institutions to design their products toward greater flexibility.

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Tables and Figures

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 (%)	84.7	-	89.2	-	83.3	-
Age (in year)	30.9	10.5	28.4	10.9	31.6	10.3
Lenght of time with SafeSave (in year)	1.8	1.4	0.9	1.0	2.1	1.4
Occupational categories (%):						
irregular job	43.4	-	34.6	-	46.0	-
regular job	11.9	-	11.4	-	12.1	-
no occupation	44.7	-	54.0	-	41.9	-
Location (%):						
Gonoktuli	19.0	-	18.9	-	19.0	-
Kurmitola	26.1	-	24.9	-	26.4	-
Millat	30.1	-	32.7	-	29.4	-
Muslim	24.8	-	23.5	-	25.1	-
Saving						
Total savings balances (in BDT)	1,253	793	603	744	1,447	699
Liquid savings balances (in BDT)	581	539	603	744	575	461
Average size of deposits (in BDT)	45	78	38	78	47	78
Average size of withdrawals (in BDT)	724	765	661	845	741	741
Number of deposits per month	3.89	5.56	6.12	6.46	3.58	5.36
Number of withdrawals per month	0.15	0.41	0.20	0.46	0.14	0.40
Borrowing						
Outstanding loan balances (in BDT)	2,014	1,703	0	0	2,616	1,480
Average loan size (in BDT)	4,450	1,454	0	0	4,450	1,454
Average size of loan repayments (in BDT)	236	353	0	0	236	353
Number of loans taken per month	0.04	0.20	0.00	0.00	0.05	0.22
Number of repayments per month	1.79	3.68	0.00	0.00	2.03	3.86

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 and standard deviation of the distribution of individuals' average characteristic. All monetary figures are in BDT. BDT 80 = about US$ 1.
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Table 2
Hartal effect on savings (global sample)

Dependent variable	(1) Daily deposits	(2) Daily withdrawals	(3) Daily liquid savings balances
Lagged (dependent variable)			0.977***
			(0.001)
Trend	-0.005***	0.000	-0.003***
	(0.000)	(0.000)	(0.001)
Trend square	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	0.334***	-0.006	-0.180
	(0.061)	(0.080)	(0.128)
H1	0.379***	-0.275	0.409
	(0.133)	(0.182)	(0.311)
H2	-0.259	0.081	-0.846*
	(0.166)	(0.296)	(0.447)
1 day after H	-0.286**	-0.040	-1.028***
	(0.133)	(0.227)	(0.350)
2 days after H	0.325**	-0.454**	0.395
	(0.148)	(0.196)	(0.372)
3 days after H	0.146	-0.189	-0.578
	(0.140)	(0.213)	(0.375)
Mean dependent variable	4.022	3.239	576.439
Observations	10,167,599	10,167,599	8,082,307
Number of individuals	10,631	10,631	10,627
R-squared	0.001	0.000	0.958
Individual FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month FE	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: FE panel regressions among the whole sample. 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table 3
Hartal effect on borrowing (borrowers)

Dependent variable	(1) Daily repayments	(2) Daily loans taken	(3) Daily outstanding loan balances
Lagged (dependent variable)			0.984***
			(0.000)
Trend	-0.004***	-0.015***	-0.006***
	(0.000)	(0.001)	(0.001)
Trend square	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	-0.124	-0.165	-0.266
	(0.123)	(0.250)	(0.320)
H1	0.604**	-0.269	-0.872
	(0.291)	(0.655)	(0.771)
H2	-0.587**	-0.622	0.436
	(0.289)	(0.721)	(0.774)
1 day after H	-0.267	0.865	0.722
	(0.302)	(0.761)	(0.830)
2 days after H	0.030	-0.615	-1.072
	(0.295)	(0.631)	(0.959)
3 days after H	-0.188	1.121	1.233
	(0.283)	(0.738)	(0.887)
Mean dependent variable	8.236	9.867	2,691.060
Observations	8,972,332	8,972,332	7,133,008
Number of individuals	8,184	8,184	8,180
R-squared	0.000	0.000	0.970
Individual FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month FE	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: FE panel regressions among the group of borrowers. 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table 4
Hartal effect on cash-ins and cash-outs

Dependent variable	(1) Cash-ins	(2) Cash-outs
Trend	-0.008***	-0.013***
	(0.000)	(0.001)
Trend square	0.000***	0.000***
	(0.000)	(0.000)
Hartal effect		
Preparation period	0.265**	0.067
	(0.124)	(0.268)
H1	0.566*	-0.806
	(0.306)	(0.663)
H2	-0.812*	-0.195
	(0.421)	(0.912)
1 day after H	-0.806**	0.924
	(0.346)	(0.750)
2 days after H	0.334	-1.093
	(0.309)	(0.671)
3 days after H	-0.256	1.215*
	(0.327)	(0.708)
Mean dependent variable	11.290	11.946
Observations	10,167,599	10,167,599
Number of individuals	10,631	10,631
R-squared	0.000	0.000
Individual FE	Y	Y
Day-of-week FE	Y	Y
Week-of-Gregorian-month FE	Y	Y
Week-of-Islamic-year FE	Y	Y

Notes: FE panel regressions among the whole sample. 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table 5
Loan repayment performance

Panel A. SafeSave repayment performance

	Assets BDT Mil[1]	Interest rate on loans %[2]	PAR (30 days) %[3]	Write-off Ratio %[3]	CRR %[3]
SafeSave	130	30-36	3.8	0.70	96.18

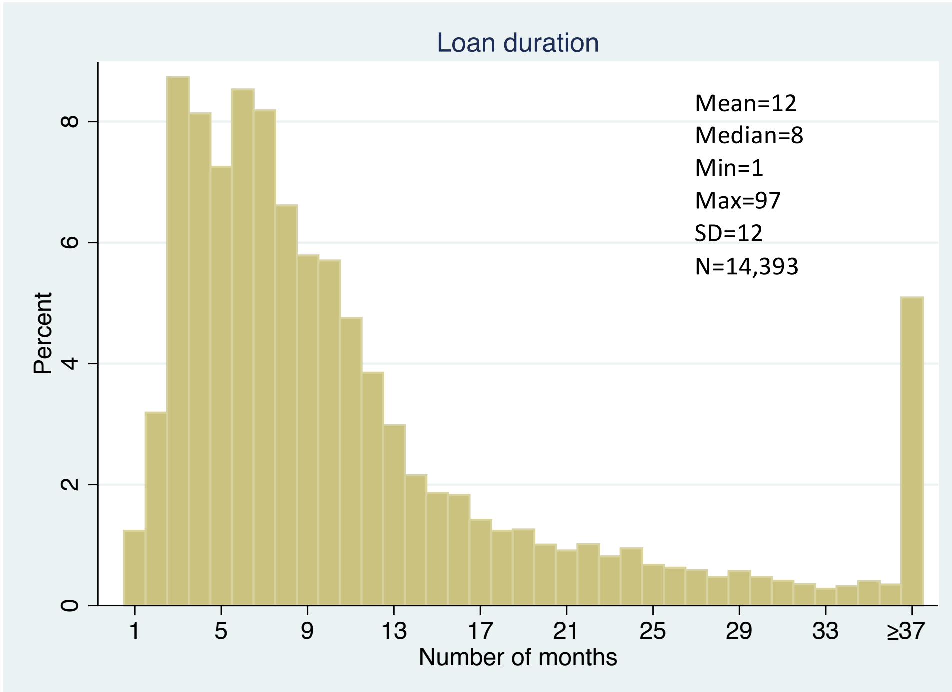
[1] Last audited financial report available in the website relative to year 2013.
[2] From 1st June 2012, SafeSave reduced the interest rate from 3% to 2.5% for the clients with loans up to BDT 5,000 or loan outstanding balance is BDT 5,000 or less.
[3] Indicators relative to the 1/2004 to 8/2012 observation period and computed for the monthly payments of interests.

Panel B. Largest Bangladeshi MFIs repayment performance

	Assets BDT Mil[1]	Interest rate on loans %	PAR (30 days) %[2]	Write-off Ratio %[2]	CRR %[3]
ASA	116,766	25	2.54-3.41	0.19-0.45	96.89
BRAC	118,333	18-27	3.79-6.12	1.74-1.84	n.a.
Grameen	200,961	20	0.99-10.66	n.a.	97.86
BURO	27,194	27	2.62-3.31	0.00-0.73	98.15

[1] Last audited financial report available in the website: for Grameen Bank, 2014; for ASA and BRAC, 2015; for BURO 2016.
[2] Data retrieved from Mix Market, except for ASA where we looked at Annual Reports. Data are relative to years 2013, 2014, and 2015.
[3]Various sources, in the web.

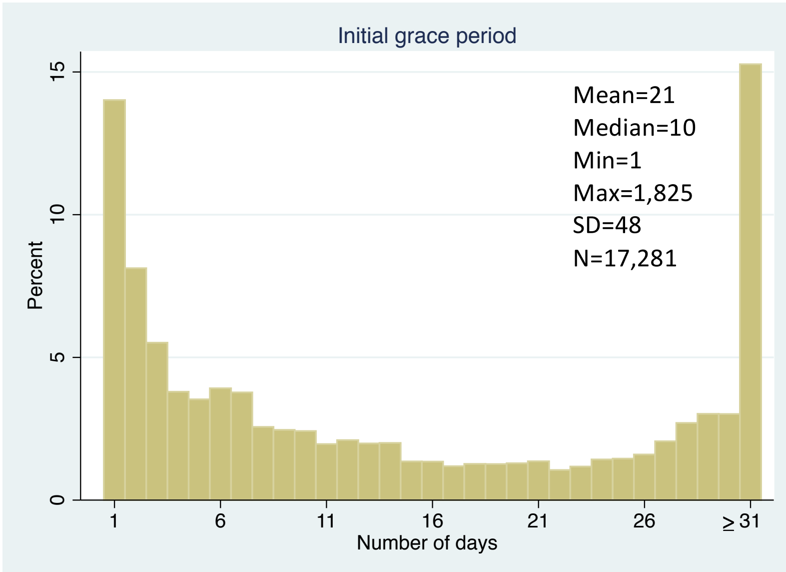
Figure 1
Distribution of loans by duration



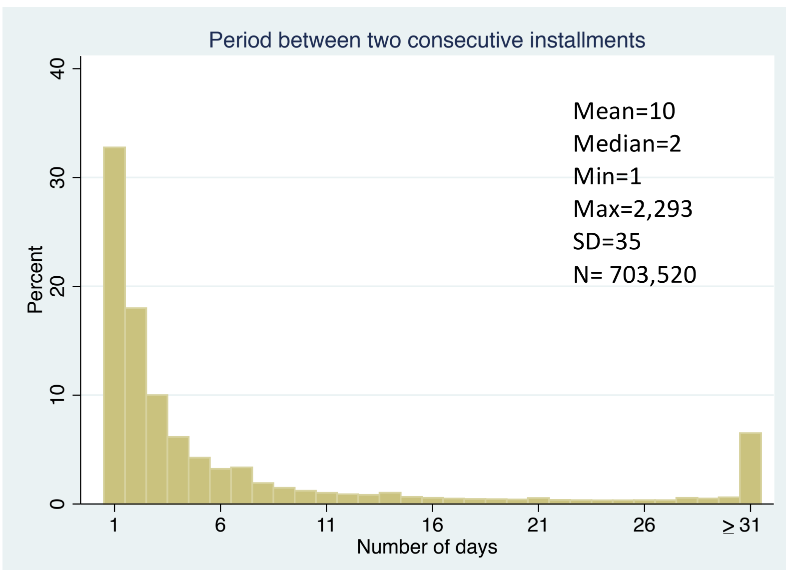
Notes: Figure 1 displays the distribution of loan duration. The total number of new loans—that were closed during the observation period—is 14,393: 37% of these loans are repaid within six months, 72% are repaid within one year, and 89% within two years. 5% of the loans are repaid in more than three years.

Figure 2
Distribution of installments by length

Panel A. Length of the initial grace period

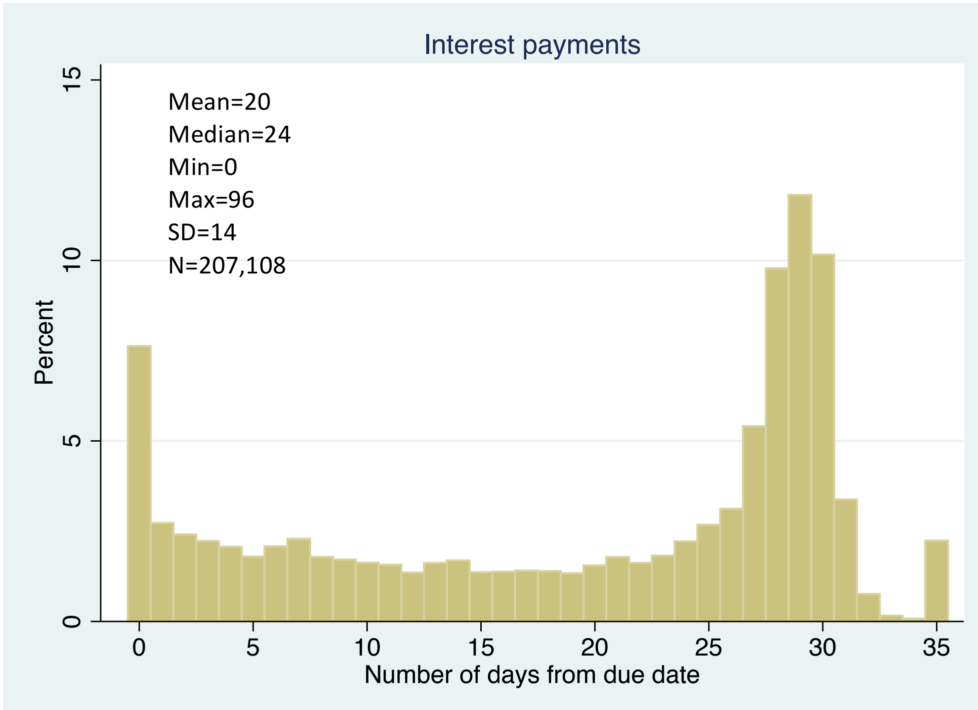


Panel B. Length between two consecutive installments



Notes: Panel A displays the length of the initial grace period, that is, the number of days from the loan disbursement till the first installment. Among the 17,281 first installments, 43% are made within seven days from disbursement, 15% more than a month after, and 5% more than two months after. Panel B displays the distribution of length between two consecutive installments. Among the 703,520 installments (excluded the initial ones), 33% take place the day following the previous payment. The median is two days after, and 7% of these time periods are longer than 30 days.

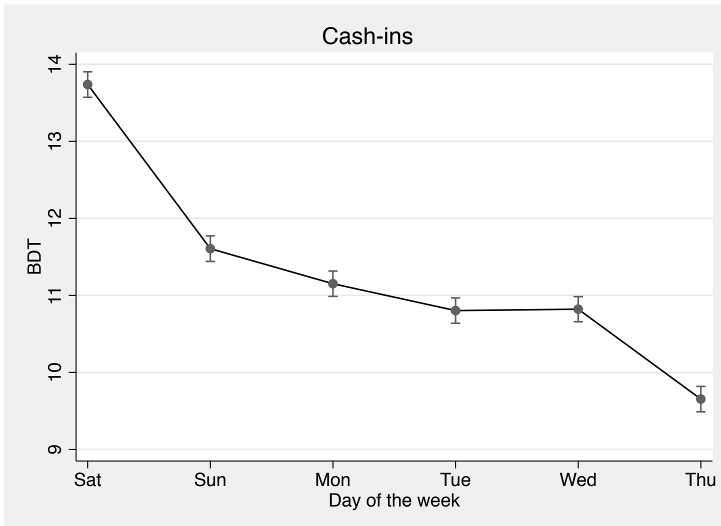
Figure 3
Distribution of interest payments by days from due date



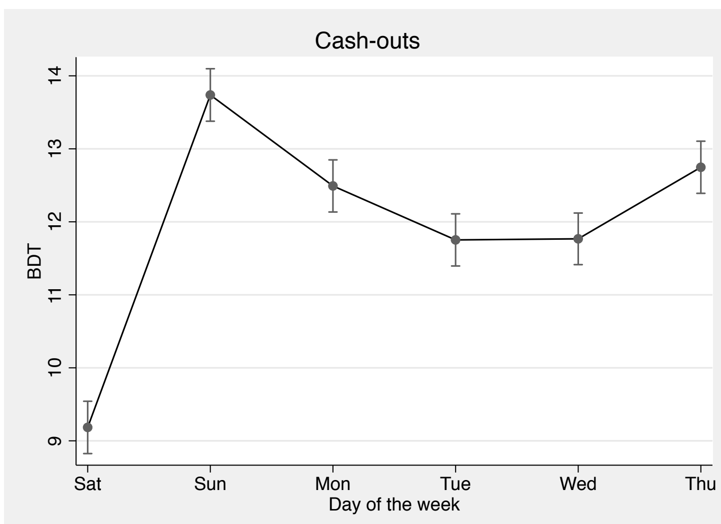
Notes: Figure 3 displays the distribution of interest payments by delayed period, that is, from due date to the day when payment occurs. The total number of interest payments is 207,108: 94% of these payments are made on time (within 30 days from the due date), 3% are one day late, and the remaining 3% are more than one day late.

Figure 4
Cash-ins, cash-outs, and day-of-week payday effect

Panel A. Cash-ins



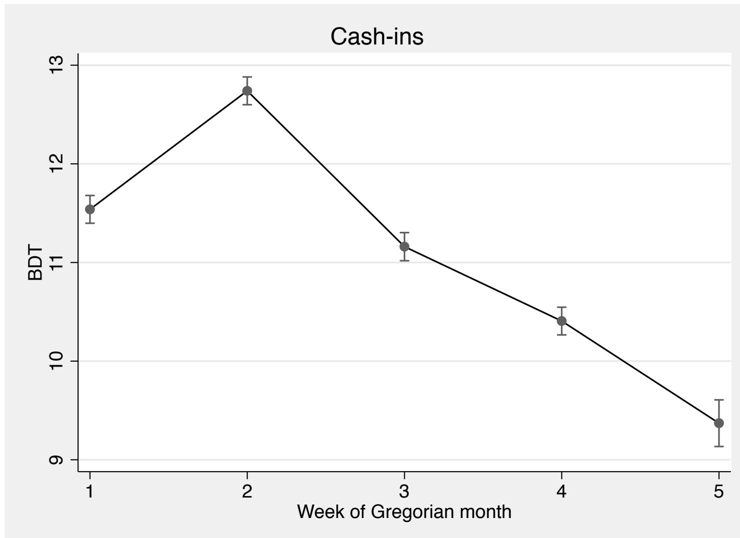
Panel B. Cash-outs



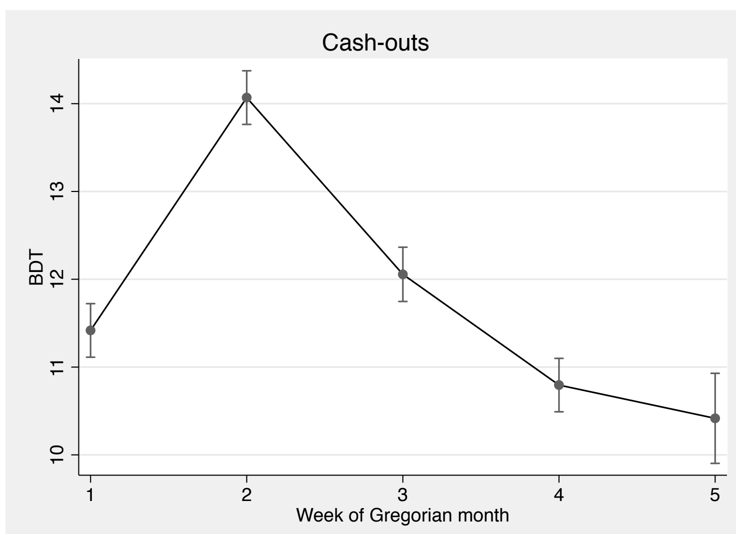
Notes: Panels A and B represent the day-of-Islamic-week FEs on the average per-client cash-ins into and cash-outs from SafeSave accounts, respectively. The *x*-axis reports the days of the Islamic week (Fridays, when SafeSave is closed, are considered missing values). The *y*-axis reports the transactions in SafeSave accounts measured in BDT. Panel A shows that cash-ins are concentrated on Saturdays, right after paydays for irregular workers, typically occurring on Thursdays. In contrast, cash-outs are rather constant throughout the working days, and low on Saturday when SafeSave discourages clients to take new loans (Panel B).

Figure 5
Cash-ins, cash-outs, and week-of-month payday effect

Panel A. Cash-ins



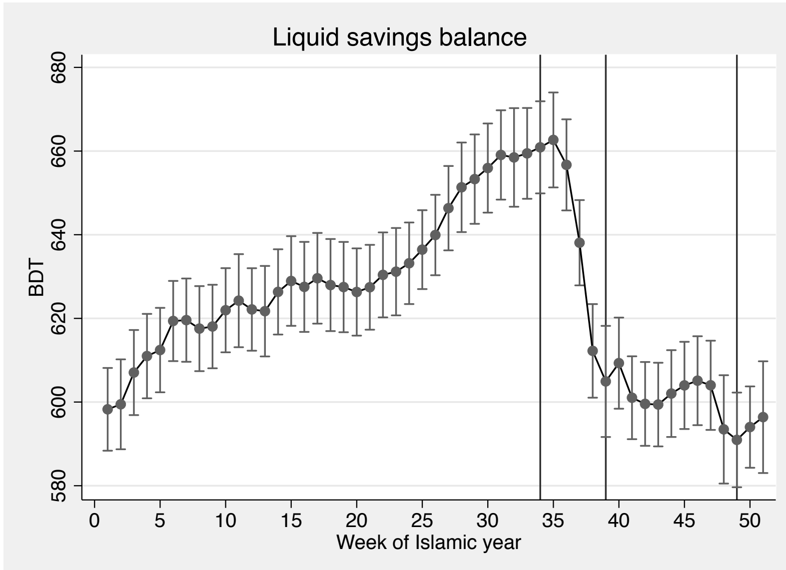
Panel B. Cash-outs



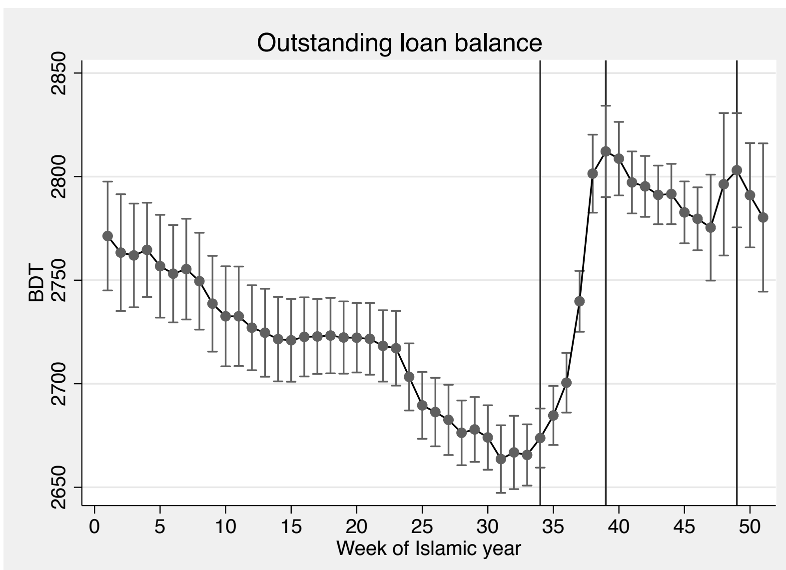
Notes: Panels A and B represent the week-of-Gregorian-month FEs on average per-client cash-ins into and cash-outs from SafeSave accounts, respectively. The x-axis reports the 1st, 2nd, 3rd, 4th, and 5th week of Gregorian months. According to Panel A, individuals make most of their cash-ins on the second week of each Gregorian month, which follows paydays for regular workers. Panel B shows that clients' cash-outs are also concentrated on the second week of the Gregorian month. This is because clients take a new loan as soon as the previous one is fully repaid.

Figure 6
Balances and Islamic festival effect

Panel A. Liquid savings balances



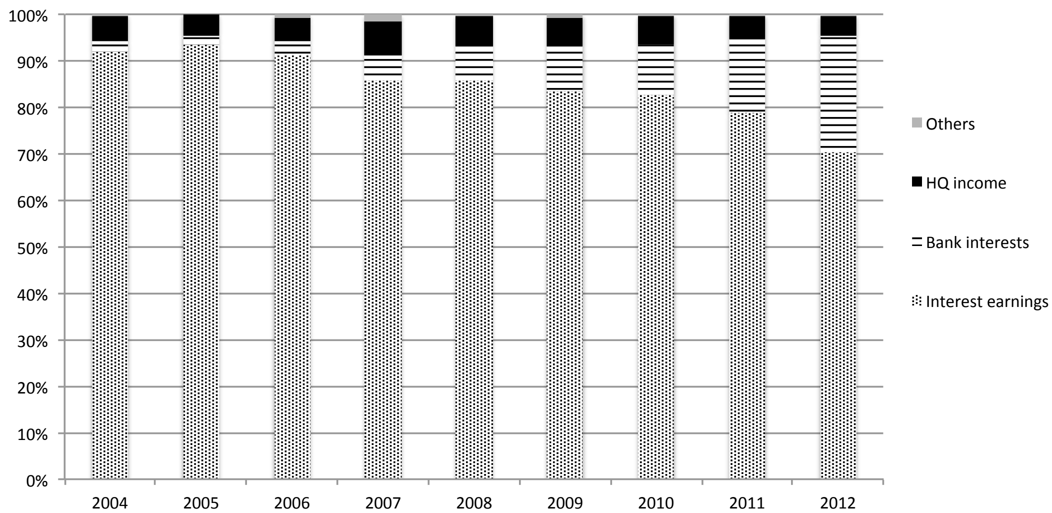
Panel B. Outstanding loan balances



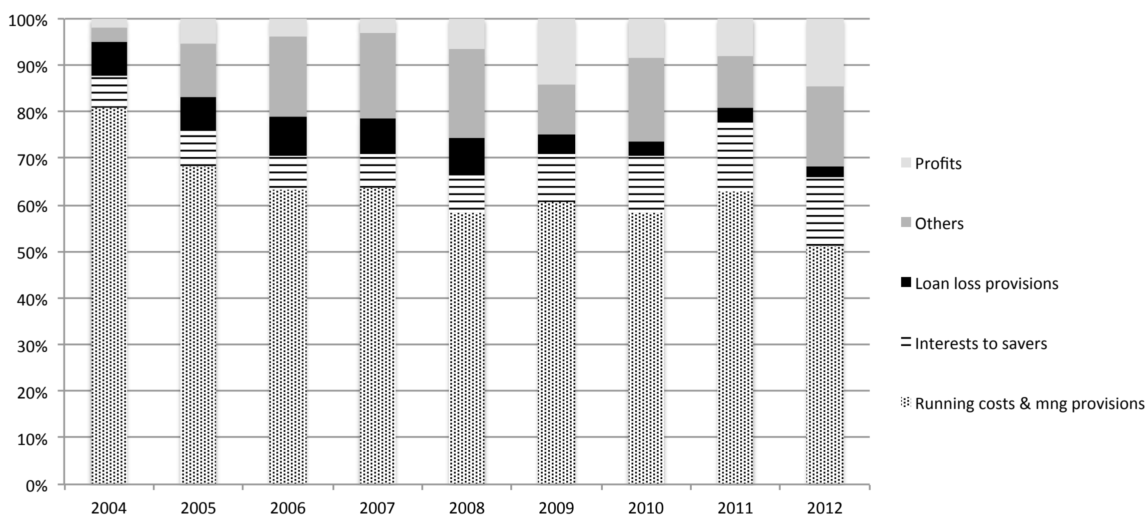
Notes: Figure 6 displays the week-of-Islamic-year FEs on the average per-client liquid savings balances (Panel A) and on the average per-borrower outstanding loan balances (Panel B). The *x*-axis reports the 51 weeks of the Islamic calendar. The *y*-axis reports balances in BDT. The vertical lines in the graphs correspond to the three Islamic festivities: month of fasting (*Ramadan*), end of the month of fasting (*Eid al-Fitr*), and date of the Feast of Sacrifice (*Eid al-Adha*). Panel A shows that SafeSave clients progressively accumulate savings in the first part of the Islamic year (until week 33) in anticipation of the *Ramadan* and *Eid al-Fitr*, during which savings balances decrease sharply (from week 34 to 39). Panel B shows that SafeSave borrowers repay their loans before *Ramadan,* and borrow extensively during *Ramadan* and *Eid al-Fitr*. Similar effects, but of smaller magnitude, occur in preparation of *Eid al-Adha (*week 49 of the Islamic year).

Figure 7
SafeSave: Revenues, costs, and profits

Panel A. Revenues



Panel B. Costs and profits



Note: Figures are percentages of total revenues.

Appendix 1. Robustness checks

We check whether results are robust across different specifications. First, we vary the sample. Second, we use a linear and a log-linear trend. Third, we aggregate data at the branch level.

A1.1 *Sample*

First, we run the econometric model in Eq. (1) varying the sample. Our baseline sample of potential borrowers excludes (from the original sample of 16,071 clients): (i) 3,827 clients that are not allowed to borrow, i.e., young people and members of the same household with borrowers; and (ii) 1,613 outliers, i.e., clients who have the 5% highest transactions and balances. As a robustness check, we add to the baseline sample SafeSave clients that are not allowed to borrow, still excluding outliers (the total number of outliers is now 1,964, as there are 351 outliers among the clients that are not allowed to borrow). Regression results confirm that SafeSave clients use the flexible accounts in response to the three shocks, i.e., paydays, Islamic festivals, and *hartals*. Figures on seasonal FEs (payday and Islamic festival effects) are not reported, as they are analogous to Figures 1, 2, and 3. Table A1 shows coefficient estimates for the *hartal* effect on savings, and Table A2 for the *hartal* effect on cash-ins and cash-outs. The group of borrowers has not changed, and so the *hartal* effect on borrowing is identical to that reported in Table 3. Estimates of the *hartal* effect using the larger sample with SafeSave clients that are not allowed to borrow are in line with the estimates using the baseline sample with only potential borrowers: the sign of the coefficients is the same; the magnitude and the significance level are slightly lower than in the baseline sample.

We then run panel regressions with a sample including the 1,613 outliers. Figure A1 reports the week-of-Islamic year FEs on savings balances and outstanding loan balances (we omitted graphs of payday FEs as they are similar to Figures 1 and 2). The *hartal* effect on savings and borrowing is reported in Tables A3 and A4, respectively. Globally, results are confirmed for borrowing behavior, but not for saving behavior. This is because the outliers (i.e. extreme values of transactions and balances) are prevalent in saving behavior but not in borrowing behavior. To show this, Figure A2 reports the average per-client savings balances and outstanding loan balances, in our baseline sample ("5% trimmed dataset") and in the sample including all the outliers ("No trimmed dataset)". The influence of outliers is particularly acute for savings balances (Panel A of Figure A2). For example, outlier values are between BDT 4,000 (US$ 50) and BDT 1,300,000 (US$ 16,250) for savings deposits; between BDT 7,900 (US$ 99) and BDT 1,700,000 (US$ 21,250) for withdrawals from savings; and between BDT 10,593 (US$ 132) and BDT 2,200,500 (US$ 27,506) for savings balances. In contrast, on the borrowing side, outlier values are between: BDT 5,750 (US$ 72) and BDT 27,600 (US$ 345) for loan repayments; and BDT 13,500

(US$ 169) and BDT 44,000 (US$ 550) for loans taken and outstanding loan balances. (During 2004-2012, the average monthly wage in Bangladesh was BDT 4,517, equivalent to US$ 56.)

Because excluding the highest 5% of the data is arbitrary, we check the robustness of results in a sample of potential borrowers that excludes clients with the 1% highest transactions and balances. Globally, results are now confirmed for both borrowing and savings behavior. Figure A3—reporting the week-of-Islamic-year FEs on saving and outstanding loan balances—is similar to Figure 3 relative to the baseline sample. Tables A5 and A6—reporting the *hartal* effect on, respectively, savings and borrowing—show that the sign of the estimates is in line with the baseline sample; the magnitude and the significance level are slightly lower than in the baseline sample.

A1.2 *Linear and log-linear trends*

Second, we run panel regressions using a linear and a log-linear trend. Globally estimates do not confirm our main result (so they are omitted). These estimates, however, should be considered invalid because adding a linear or a log-linear trend does not correct for the non-stationarity of time series. In fact, we opt for a quadratic trend because de-trended time series become stationary.

A1.3 *Aggregate data at the branch level*

We run various robustness checks at the aggregate (branch) level. Namely, we run ordinary least squares (OLS) regressions where the average per-client transactions and balances are a linear function of time FEs, quadratic trend, *hartal* dummies, branch FEs and an error term. The OLS regression at the branch level writes as:

$$Y_{btdwx} = \alpha_d + \beta_w + \gamma_x + T(t) + \mu H1_t + \pi H2_t + \sigma PreH_t + \sum_d \rho_d PostH_{d,t} + u_b + \varepsilon_{btdwx} \quad \text{(A1)}$$

where Y_{btdwx} is an (aggregate) outcome variable for branch *b* at time (day) *t*, u_b are branch FEs, ε_{btdwx} is the error term and the remaining terms are as in Eq. (1). We use weights for each branch equal to the number of clients and we vary the observation period in the following way: we consider the full observation period from 01/2004 to 08/2012. Successively, we focus on the period starting on 01/2006, when all four branches are well established and growth rates of savings balances and outstanding loan balances are constant. Our main results are robust across all these specifications.

Estimates of time FEs (paydays and Islamic festival effects) are omitted, as they are analogous to the estimates using individual saving and borrowing. Tables A7 and A8 show coefficient estimates for the *hartal* effect on saving and borrowing, respectively (estimation period starting on 01/2006). Generally, results using aggregate data are in line with results using individual data: the sign and magnitude of the *hartal* effect are equivalent; the significance level has decreased (especially for the *hartal* effect on borrowing—Table A8—which is not statistically significant).

As previously discussed, the original time series are not stationary; residuals, obtained by subtracting seasonality and a (quadratic) trend from the original time series, become stationary. We therefore check the robustness of our results using the data at the branch level and an estimation procedure in two steps. In the first step, we estimate trend and seasonality. In the second step, *d*e-trended and de-seasonalized time series (that is, residuals of the first step) are regressed on *hartal* dummies. Coefficient estimates for the *hartal* effect on savings and borrowing (Tables A9 and A10) are analogous to the estimates using OLS at the aggregate level (Tables A7 and A8).

Table A1
Hartal effect on savings
Potential and non-potential borrowers

Dependent variable	(1) Daily deposits	(2) Daily withdrawals	(3) Daily liquid savings balances
Lagged (dependent variable)			0.980***
			(0.000)
Trend	-0.004***	0.000	-0.002***
	(0.000)	(0.000)	(0.000)
Trend square	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	0.326***	-0.080	-0.093
	(0.055)	(0.073)	(0.111)
H1	0.371***	-0.203	0.345
	(0.117)	(0.173)	(0.275)
H2	-0.206	0.167	-0.758*
	(0.149)	(0.288)	(0.402)
1 day after H	-0.175	0.052	-0.880***
	(0.121)	(0.211)	(0.304)
2 days after H	0.214*	-0.424**	0.291
	(0.130)	(0.187)	(0.333)
3 days after H	0.142	-0.049	-0.604*
	(0.123)	(0.197)	(0.324)
Mean dependent variable	4.211	3.472	561.160
Observations	12,579,860	12,579,860	9,998,510
Number of panelvar_id	14,107	14,107	14,102
R-squared	0.001	0.000	0.963
Individual FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month FE	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: FE panel regressions with potential and non-potential borrowers (the latter are clients that are less that 16 years old or that belong to a borrowing household). This sample still excludes outliers (i.e., clients that have the highest 5% value of transactions and/or balances). 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table A2
Hartal effect on cash-ins and cash-outs
Potential and non-potential borrowers

Dependent variable	(1) Cash-ins	(2) Cash-outs
Trend	-0.007***	-0.012***
	(0.000)	(0.001)
Trend square	0.000***	0.000***
	(0.000)	(0.000)
Hartal effect		
Preparation period	0.289***	0.041
	(0.111)	(0.201)
H1	0.531**	-0.637
	(0.260)	(0.528)
H2	-0.632*	-0.064
	(0.335)	(0.780)
1 day after H	-0.611**	0.850
	(0.278)	(0.650)
2 days after H	0.234	-0.946*
	(0.273)	(0.512)
3 days after H	-0.170	1.102*
	(0.255)	(0.623)
Mean dependent variable	10.085	10.509
Observations	12,579,860	12,579,860
Number of individuals	14,107	14,107
R-squared	0.000	0.000
Individual FE	Y	Y
Day-of-week FE	Y	Y
Week-of-Gregorian-month FE	Y	Y
Week-of-Islamic-year FE	Y	Y

Notes: FE panel regressions with potential and non-potential borrowers (the latter are clients that are less that 16 years old or that belong to a borrowing household). This sample still excludes outliers (i.e., clients that have the highest 5% value of transactions and/or balances). 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table A3
Hartal effect on savings
All potential borrowers (including outliers)

Dependent variable	(1) Daily deposits	(2) Daily withdrawals	(3) Daily liquid savings balances
Lagged (dependent variable)			0.994***
			(0.002)
Trend	-0.005**	-0.001	-0.002
	(0.002)	(0.001)	(0.004)
Trend square	0.000**	0.000***	0.000
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	-0.204	-0.090	-0.167
	(0.312)	(0.552)	(0.957)
H1	1.170*	-0.071	1.403
	(0.599)	(0.703)	(1.109)
H2	0.320	0.041	-0.884
	(1.367)	(1.008)	(2.152)
1 day after H	0.197	0.642	-0.890
	(0.514)	(0.837)	(0.867)
2 days after H	0.187	-0.482	0.645
	(0.598)	(0.664)	(1.041)
3 days after H	0.478	-0.360	0.322
	(0.624)	(0.627)	(1.040)
Mean dependent variable	8.068	6.657	1,073.926
Observations	12,495,100	12,495,100	9,932,828
Number of panelvar_id	12,244	12,244	12,240
R-squared	0.000	0.000	0.987
Individual FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month FE	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: FE panel regressions among all potential borrowers (differently from the baseline sample, we now include the clients that have the highest 5% value of transactions and/or balances). 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table A4

Hartal effect on borrowing

All potential borrowers (including outliers)

Dependent variable	(1) Daily repayments	(2) Daily loans taken	(3) Daily outstanding loan balances
Lagged (dependent variable)			0.982***
			(0.000)
Trend	-0.002***	-0.012***	-0.001
	(0.001)	(0.001)	(0.002)
Trend square	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	-0.155	-0.394	-0.042
	(0.161)	(0.324)	(0.412)
H1	1.182***	-0.137	-1.318
	(0.422)	(0.924)	(1.126)
H2	-1.334***	1.034	1.906
	(0.475)	(1.441)	(1.564)
1 day after H	-1.018***	0.510	0.863
	(0.371)	(1.019)	(1.099)
2 days after H	-0.058	-0.813	-1.384
	(0.396)	(0.881)	(1.289)
3 days after H	-0.507	1.434	1.925
	(0.367)	(1.047)	(1.242)
Mean dependent variable	12.381	14.439	3,089.091
Observations	11,072,612	11,072,612	8,803,041
Number of individuals	9,564	9,564	9,560
R-squared	0.000	0.000	0.967
Individual FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month FE	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: FE panel regressions among all potential borrowers (differently from the baseline sample, we now include the clients that have the highest 5% value of transactions and/or balances). 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table A5
Hartal effect on savings
Potential borrowers, excluding the top 1% clients

Dependent variable	(1) Daily deposits	(2) Daily withdrawals	(3) Daily liquid savings balances
Lagged (dependent variable)			0.985***
			(0.001)
Trend	-0.005***	-0.000	-0.001***
	(0.000)	(0.000)	(0.001)
Trend square	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	0.275***	-0.081	-0.142
	(0.089)	(0.121)	(0.179)
H1	0.512**	0.471	-0.105
	(0.203)	(0.368)	(0.518)
H2	-0.019	0.248	-1.072*
	(0.275)	(0.425)	(0.618)
1 day after H	-0.129	-0.141	-0.547
	(0.228)	(0.335)	(0.482)
2 days after H	0.122	-0.633**	0.488
	(0.186)	(0.274)	(0.514)
3 days after H	0.132	0.005	-0.682
	(0.185)	(0.338)	(0.530)
Mean dependent variable	5.568	4.550	760.755
Observations	11,880,107	11,880,107	9,443,829
Number of panelvar_id	11,855	11,855	11,851
R-squared	0.000	0.000	0.971
Individual FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month FE	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: FE panel regressions among potential borrowers, excluding the clients that have the highest 1% value of transactions and/or balances (differently, in the baseline sample, we exclude the top 5% clients). 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table A6

Hartal effect on borrowing

Potential borrowers, excluding the top 1% clients

Dependent variable	(1) Daily repayments	(2) Daily loans taken	(3) Daily outstanding loan balances
Lagged (dependent variable)			0.984***
			(0.000)
Trend	-0.004***	-0.014***	-0.004***
	(0.001)	(0.001)	(0.001)
Trend square	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	-0.109	-0.196	-0.154
	(0.142)	(0.293)	(0.370)
H1	0.618*	-0.480	-1.208
	(0.345)	(0.805)	(0.949)
H2	-0.753	1.076	1.272
	(0.469)	(1.296)	(1.391)
1 day after H	-0.629*	0.570	0.338
	(0.353)	(0.931)	(1.014)
2 days after H	0.011	-0.216	-0.908
	(0.361)	(0.821)	(1.201)
3 days after H	-0.277	1.204	1.295
	(0.349)	(0.926)	(1.102)
Mean dependent variable	10.601	12.508	2,931.674
Observations	10,522,794	10,522,794	8,365,846
Number of individuals	9,228	9,228	9,224
R-squared	0.000	0.000	0.969
Individual FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month FE	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: FE panel regressions among all potential borrowers, excluding clients that have the highest 1% values of transactions and/or balances (differently, in the baseline sample, we exclude the top 5% clients). 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table A7
Hartal effect on savings
OLS regression at branch level

Dependent variable	(1) Daily deposits	(2) Daily withdrawals	(3) Daily liquid savings
Trend	-0.004***	-0.003***	-0.155***
	(0.000)	(0.000)	(0.004)
Trend square	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	0.150**	0.045	-10.326***
	(0.066)	(0.110)	(1.276)
H1	0.234	-0.223	-7.714**
	(0.189)	(0.225)	(3.599)
H2	-0.481**	0.115	-2.180
	(0.204)	(0.328)	(4.914)
1 day after H	-0.405***	0.062	-9.922**
	(0.157)	(0.301)	(4.078)
2 days after H	0.285	-0.346	-3.627
	(0.211)	(0.239)	(3.721)
3 days after H	0.139	-0.166	-5.589
	(0.164)	(0.272)	(3.576)
Mean dependent variable	3.943	3.200	588.270
Observations	7,832	7,832	7,832
R-squared	0.327	0.133	0.977
Branch FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month FE	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: OLS regressions at branch level, among the baseline. 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table A8
Hartal effect on borrowing
OLS regression at branch level

Dependent variable	(1) Daily repayments	(2) Daily loans taken	(3) Daily outstanding loan balances
Trend	-0.008***	-0.010***	-0.260***
	(0.000)	(0.001)	(0.012)
Trend square	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Hartal effect			
Preparation period	-0.102	-0.035	-0.945
	(0.172)	(0.327)	(4.134)
H1	0.364	-1.287	-7.116
	(0.467)	(0.995)	(11.338)
H2	-0.778	0.710	-17.793
	(0.582)	(1.626)	(13.630)
1 day after H	-0.591	0.594	-3.485
	(0.513)	(1.173)	(12.604)
2 days after H	0.465	-0.293	-12.685
	(0.476)	(0.775)	(11.167)
3 days after H	-0.237	1.839*	-5.036
	(0.451)	(1.103)	(12.431)
Mean dependent variable	8.384	9.850	2,734.830
Observations	7,832	7,832	7,832
R-squared	0.282	0.251	0.929
Branch FE	Y	Y	Y
Day-of-week FE	Y	Y	Y
Week-of-Gregorian-month F	Y	Y	Y
Week-of-Islamic-year FE	Y	Y	Y

Notes: OLS regressions at branch level, among the baseline sample. 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Table A9

Hartal effect on savings

OLS regression at branch level, residuals

Dependent variable	(1) Daily deposits	(2) Daily withdrawals	(3) Daily liquid savings balances
Hartal effect			
Preparation period	0.273***	-0.016	-11.326***
	(0.077)	(0.095)	(1.649)
H1	0.447*	-0.177	-10.620**
	(0.257)	(0.228)	(4.970)
H2	-0.387*	0.263	-1.343
	(0.221)	(0.311)	(6.035)
1 day after H	-0.175	0.028	-12.319**
	(0.194)	(0.294)	(5.527)
2 days after H	0.545**	-0.384*	-5.150
	(0.247)	(0.215)	(4.947)
3 days after H	0.255	-0.278	-9.183*
	(0.199)	(0.246)	(5.239)
Mean dependent variable	3.943	3.200	588.270
Observations	7,832	7,832	7,832
R-squared	0.004	0.001	0.010

Notes: OLS regressions at branch level, among the baseline sample. Dependent variables are de-trended and de-seasonalized time-series. 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 US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

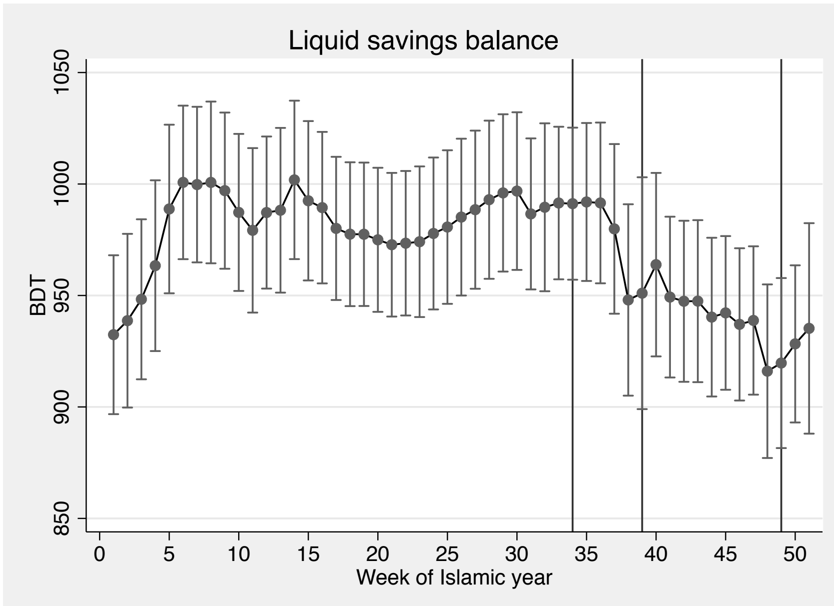
Table A10
Hartal effect on borrowing
OLS regression at branch level, residuals

Dependent variable	(1) Daily repayments	(2) Daily loans taken	(3) Daily outstanding loan balances
Hartal effect			
Preparation period	-0.130	0.322	-29.664***
	(0.168)	(0.359)	(7.023)
H1	0.164	-1.461	-42.620**
	(0.495)	(0.978)	(21.603)
H2	-0.502	0.443	-21.480
	(0.666)	(1.656)	(19.753)
1 day after H	-0.556	0.998	-37.990
	(0.557)	(1.446)	(24.916)
2 days after H	0.319	-0.067	-35.774*
	(0.516)	(0.882)	(20.933)
3 days after H	-0.108	2.486**	-41.433*
	(0.451)	(1.147)	(24.165)
Mean dependent variable	8.384	9.850	2,734.830
Observations	7,832	7,832	7,832
R-squared	0.000	0.001	0.008

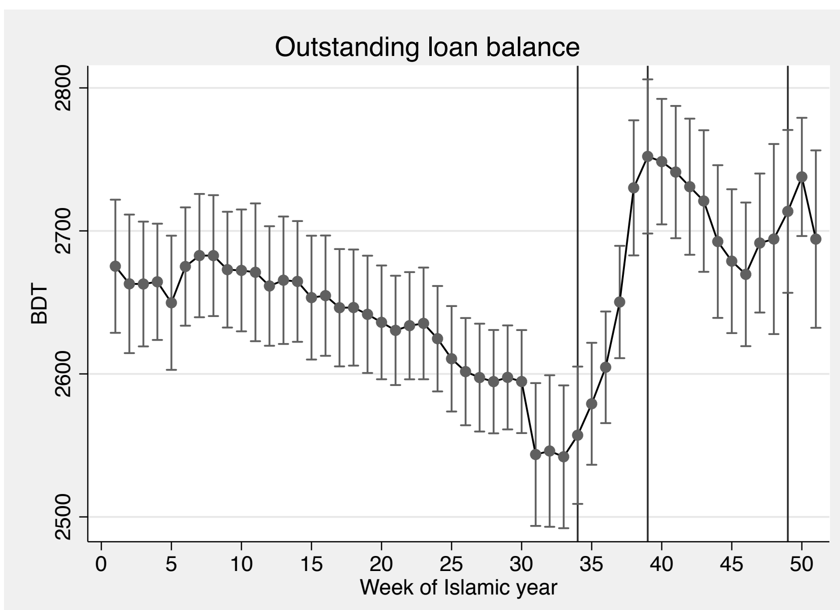
Notes: OLS regressions at branch level, among the baseline sample. Dependent variables are de-trended and de-seasonalized time-series. Robust standard errors are reported in parentheses. Level of significance is: ***p<0.01, ** p<0.05, *p<0.1. All financial figures are in BDT. BDT 80 = about US$ 1. Preparation period starts when a *hartal* event (H) is announced. H1 indicates the first day of *hartal*; H2 indicates the days of *hartal* following the first one.

Figure A1
Balances and Islamic festival effect
All potential borrowers (including outliers)

Panel A.



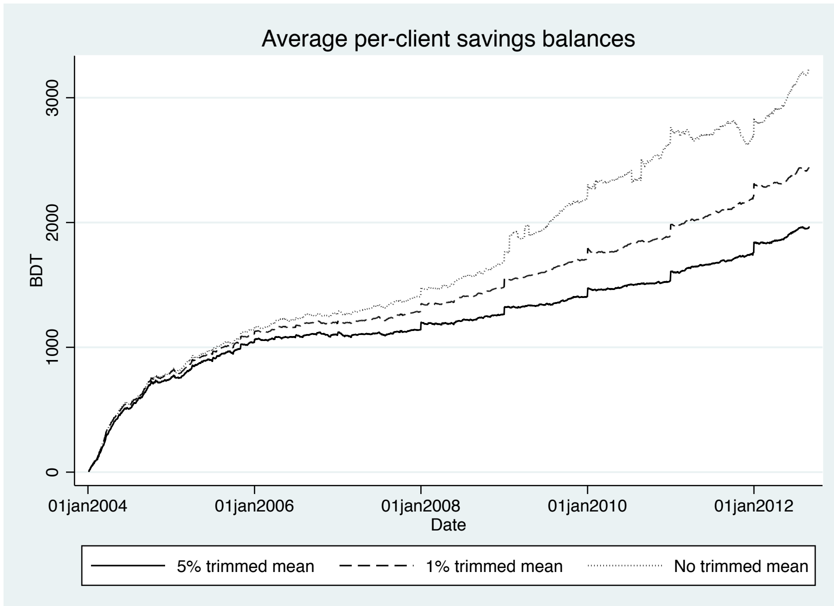
Panel B.



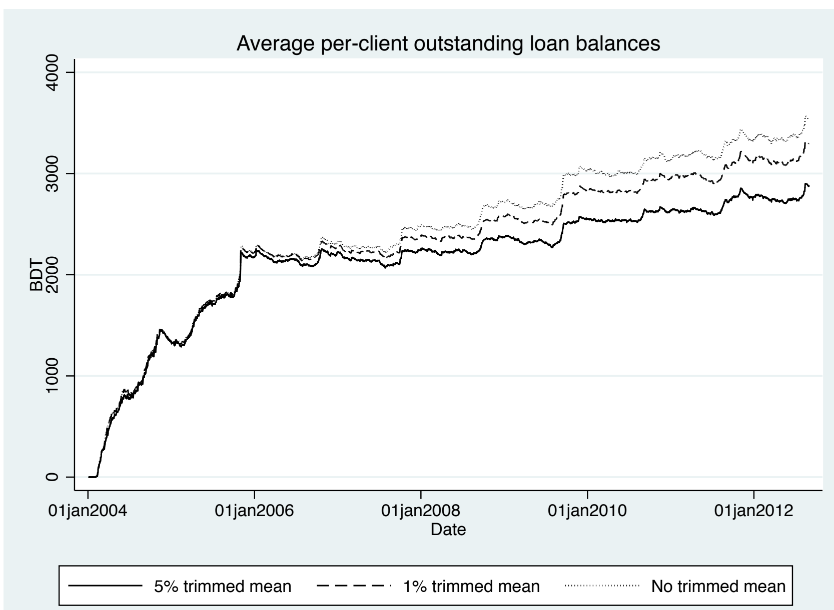
Notes: Figure A1 displays the week-of-Islamic-year FEs on liquid savings balances (Panel A) and on the outstanding loan balances (Panel B). The *x*-axis reports the 51 weeks of the Islamic calendar. The *y*-axis reports balances in BDT. The vertical lines in the graphs correspond to the three Islamic festivities: month of fasting (*Ramadan*), end of the month of fasting (*Eid al-Fitr*), and date of the Feast of Sacrifice (*Eid al-Adha*). The sample is composed of all potential borrowers (differently, in the baseline sample, we exclude the top 5% clients).

Figure A2
Average per-client balances, by sample size

Panel A.



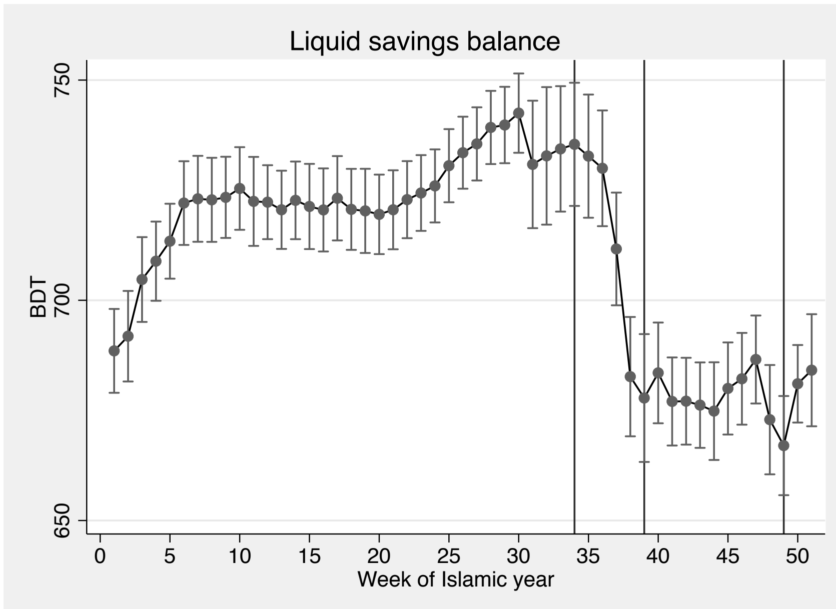
Panel B.



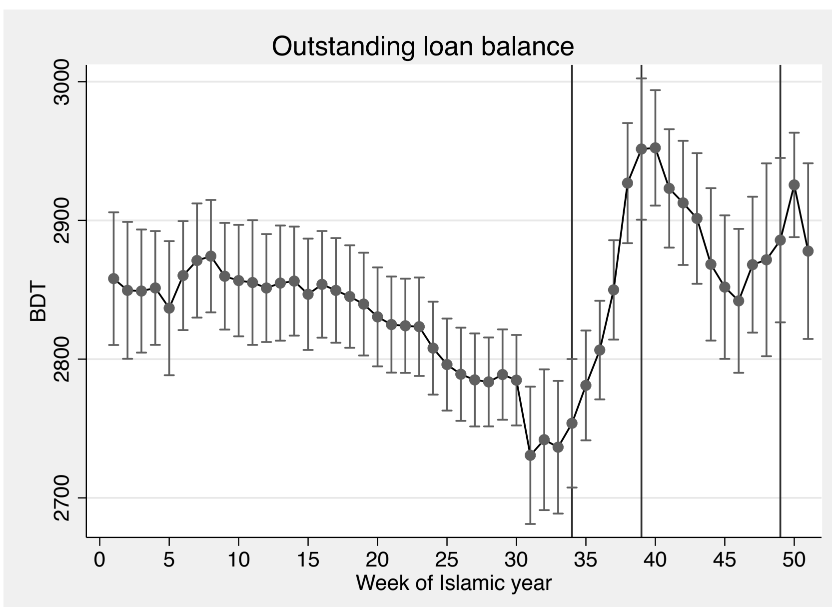
Notes: Figure A2 displays the dynamics of the average per-client liquid savings balances (Panel A) and outstanding loan balances (Panel B) in the observation period (01/2004 – 08/2012). The three lines are relative to different sample definitions: all potential borrowers ("no trimmed mean"), excluding the top 1% clients ("1% trimmed mean"), and excluding the top 5% clients ("5% trimmed mean"). Baseline sample is "5% trimmed mean".

Figure A3
Balances and Islamic festival effect
Potential borrowers, excluding the top 1% clients

Panel A.



Panel B.



Notes: Figure A3 displays the week-of-Islamic-year FEs on liquid savings balances (Panel A) and on the outstanding loan balances (Panel B). The *x*-axis reports the 51 weeks of the Islamic calendar. The *y*-axis reports balances in BDT. The vertical lines in the graphs correspond to the three Islamic festivities: month of fasting (*Ramadan*), end of the month of fasting (*Eid al-Fitr*), and date of the Feast of Sacrifice (*Eid al-Adha*). The sample is composed of potential borrowers, excluding clients that have the highest 1% values of transactions and/or balances (differently, in the baseline sample, we exclude the top 5% clients).