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FINTECH AND HOUSEHOLD RESILIENCE TO SHOCKS: EVIDENCE FROM DIGITAL LOANS IN KENYA

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ABSTRACT

Developing country lenders are taking advantage of fintech tools to create fully digital loans on mobile phones. Using administrative and survey data, we study the take up and impacts of one of the most popular digital loan products in the world, M-Shwari in Kenya. While 34% of those eligible for a loan take it, the loan does not substitute for other credit. The loans improve household resilience: households are 6.3 percentage points less likely to forego expenses due to negative shocks. We conclude that while digital loans improve financial access and resilience, they are not a panacea for greater credit market failures.

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I. Introduction

Economists have long noted the importance of access to credit for consumption smoothing. While access to credit during a time of financial need can play an important role in improving welfare, the high cost of credit provision – due to information asymmetries, fixed costs, etc. – is an often noted barrier in both developed and developing countries. The importance of access to credit for consumption smoothing purposes is even more salient in developing countries where income is subject to shocks, where social safety nets are few and unreliable and other financial substitutes are negligible, and where the outcomes of income fluctuations can be more severe. In this paper, we are the first to study the effects of a major innovation in the world of consumer finance in a developing country that dramatically lowers the costs of access and provision of credit: digital loans.

Digital loans accessed and delivered through mobile phones hold promise in this area as they substantially lower some of the costs associated with access to credit on the household side and also reduce the administrative costs of loans from a lender's perspective.[1] In addition, in the spirit of the growth of fintech, with the advance of novel data sources, banks may find it easier to score potential borrowers and offer products that leverage pre-existing mobile platforms, thus reducing the information asymmetries (Bjorkegren and Grissen 2018) and providing smaller and cheaper loans. Digital loans therefore have the potential to help households facing shocks smooth consumption by instantaneous access to loans, and given their overall lower cost (compared to payday loans or village money lenders), are also less likely to put households into a harmful cycle of debt and bankruptcy. This paper finds high take up of small digital loans among individuals eligible for it, not crowding out of other forms of credit, and also finds that access to this product increases household resilience in the face of negative shocks.

The product we study, M-Shwari, is a fully digital bank account operating over the rails of mobile money (called M-PESA). It was launched in 2012 through a partnership between the

[1] One potential reason (among many possible contenders) for the low take up of microfinance in some settings could be the fixed costs associated with accessing and obtaining loans from microfinance institutions, whether in the form of group lending dynamics or other access related costs of borrowing.

Commercial Bank of Africa (CBA) and Safaricom (the largest telecom provider) in Kenya. The take up of M-Shwari has been remarkable: within two years of the launch of the product there were more than 4.5 million active users (nearly 20% of the adult population) and approximately 10 million accounts had been opened. M-Shwari is credited with making the Commercial Bank of Africa a major player in the lending market: as of 2017, CBA had over 50% of the loan account market share in Kenya (Central Bank of Kenya Statistics, 2017). A major draw for signing up for M-Shwari is the loan product where approved customers have access to small, short-term (30 day, 7.5% monthly interest rate)[2] loans even if they had no banking or credit history. The average M-Shwari loan size (conditional on having a loan) for individuals in our study sample is around KSh 480 (approximately 4.8 USD) and the average total value of all loans taken out over 18 months on M-Shwari is KShs 4,000 (approximately 40 USD). [3]

To estimate the take up and impacts of these loans we use a regression discontinuity (RD) design. M-Shwari loans are issued based on a strict cutoff in the credit score assigned to customers as soon as they open an M-Shwari account (*not* when they chose to borrow). This score is unknown to the M-Shwari customer. All the customer knows is whether he/she is eligible for a loan and how much he/she has been approved for (i.e. the credit limit). This allows us to use an RD design to evaluate the impacts of access to credit. We show empirically that people who just qualify and those who barely missed the qualification cutoff are similar along various observable characteristics. This is to be expected if the credit score threshold is determined exogenously (or through a complex formula where some of these characteristics might be inputs) and if people are unable to specifically manipulate their scores to fall on one side of the cutoff.

For the analysis, we use a combination of survey and administrative data. For the surveys (conducted in September 2016-January 2017), we draw a sample of customers who opened an account nearly two years before the survey (between January and March 2015). In these two years, some individuals who were initially unqualified to receive credit eventually become eli-

[2]As a comparison, the implied annual interest rates for payday loans in the US are between 400-1000% (Stegman 2007).

[3]M-Shwari loans constitute a significant fraction of overall loans held by households: in our survey data, the average overall debt taken out by households over the one year prior to the survey is around KSh 16,000.

gible for the digital loan.[4] As the take up of the loan is endogenously determined, we only use the credit score threshold *at the time the individual opened the account* to assign probability of treatment. Not everyone who has a credit score above the cutoff takes out a loan; hence, incomplete compliance implies a fuzzy RD design and we estimate intent to treat (ITT) effects.

Our results provide several important insights into the impacts of access to digital loans, including the take up of loans.[5] First, access to M-Shwari results in a meaningful expansion of credit for eligible households. Individuals who qualify for loans are nearly 11 percentage points more likely to take a loan of any kind (digital or otherwise), off a base of 46% in the control group who have any loans at all (i.e. from across all loans). Second, this increase in household credit is entirely due to M-Shwari and we find no evidence of substitution from other forms of credit (such as informal loans, loans from non-digital bank accounts, or loans from peer-to-peer banking). M-Shwari has an overall take up of nearly 34% among the eligible population we study in this paper and within two years (between the opening of the account and our survey), those who initially qualified for M-Shwari have more 37% more loans.[6]

Finally, our most important insight on the impact of greater access and receipt of digital loans is on resilience. Households who are eligible for the loan, while not more likely to *face* negative shocks in the 6 months prior to the survey, are significantly less likely to forego expenditures conditional on having a negative shock.[7] Note that nearly 90% of our sample report having experienced one of these negative shocks over the last 6 months. Households eligible for M-Shwari are 6.3 percentage points less likely to forego any expenses in response to a negative shock (approximately 68% of the control group reports having to forego some expenses

[4]Within the M-Shwari system, the individual's credit score does not change, but those below the credit score can save in their accounts to later become eligible for a loan. Since the customer does not know their credit score, all they see is a change in their credit limit.

[5]In this paper we use the terms "digital loans" and "loans from M-Shwari" interchangeably. There are other, non-M-Shwari digital loan products; however, in our sample, 93% of all digital loans are M-Shwari loans.

[6]We do not study the universe of eligible population. This is because we use an RD design and restrict our surveys and results to a specific bandwidth around the eligibility cutoff. Hence, the eligible population in our case is a population that would just be qualified to get a loan and perhaps the more vulnerable populations typically targeted by microfinance institutions anyway.

[7]We measure negative shocks by asking households about the death of a household member, the illness of household member, accidental injury, the loss of employment, violent injury, the failure/loss of business, livestock death, crop disease /pests, theft/robbery/burglary/assault, fire/house destroyed/damaged, and drought/floods, all in the 6 months prior to the survey date.

in response to a negative shock). Examining finer categories, they are also less likely to forego expenses on meals, medicines, and non-food items, although these individual results are not statistically significant under multiple hypothesis testing.

We also look at consumption to understand where in a household's budget the loans may be spent. We find an increase in the propensity to spend on education. Although this may seem surprising at first, looking at the data, households report spending the loan, quite often, on emergencies, especially health events. However, even though households spend the actual loan money on, say, medication, the marginal dollar from the loan gets spent on the item they would have adjusted had they not had access to the loan. This happens to be education, a result that is consistent with Jack and Suri (2014) and Suri et al (2012) who find similar effects when studying how M-PESA affects consumption smoothing.

We find economically and statistically insignificant impacts on a host of other outcomes such as savings and asset ownership, suggesting that at least for the affected population around the credit cut-off, access to digital credit is not necessarily transformative. However, given the size of these loans, this is to be expected. Similarly, the size of these loans being small is also in line with eligible households not being overburdened by debt due to increased access to credit: the ratio of interest to consumption over a one year period conditional on having a loan is only 1.2%.

The results on take up are an important contribution to the literature on household finance in developing countries, most of which has focussed on the issue of relatively low take up in the context of microfinance (see Banerjee et al 2015). In our survey, households have extremely poor access to any form of formal credit. Only 6% have had a bank loan over the two years prior to the survey, only 2% have had a microfinance loan, only 5% have had a loan from a savings and credit cooperative and only 6% from a ROSCA (peer to peer lending). In addition, we find that M-Shwari does not substitute for other forms of finance, but truly expands credit access. Taken together, this suggests that ease of access due to mobile technology could be an extremely important feature for expanding credit access to populations who do not have access to formal finance.

Our results on resilience contribute towards an understanding of the role of small, short term credit in developed and developing countries. Research in consumer finance on payday loans in the US for example, finds that while access to credit allows individuals to smooth during certain shocks (Morse 2009, Zinman 2010), the high interest rates charged by these loans often end up harming borrowers (Skiba and Tobacman 2009, Melzer 2011). Perhaps as a way to resolve this concern, many researchers have focussed their attention on regulation of interest rates in this area or behavioral tools that might help borrowers make better decisions regarding payday loans (Zinman 2010, Bertrand and Morse 2011). Our results add to this rich space by showing that fintech innovations in developing countries can dramatically lower the costs associated with lending and borrowing, leading to high take up and improvements in household resilience.

In the developing country context, Karlan and Zinman (2011) found that net borrowing increased when microfinance clients were offered individual (as opposed to group) liability loans, but both business activity and subjective well-being fell as a result, although the loans helped borrowers cope with risk. Tarozzi et al. (2013) report similarly mixed evidence of access to microcredit in Ethiopia, although Karlan and Zinman (2010) document that access to consumer loans improved consumption and some measures of mental health. At a more macro level, Pande and Burgess (2005) study the expansion of the rural bank branch network in India and find that it resulted in reduced rural poverty, both through higher deposit mobilization and credit disbursement. Suri and Jack (2016) report on the poverty effects of the expansion of mobile money in rural Kenya, and in their 2014 paper they find evidence that support networks operate more efficiently in reducing risk in the presence of mobile money.

While we find effects on resilience, the lack of effects on investments and savings is in line with the broader literature on microfinance in developing countries. High returns to capital, as documented for example by de Mel, McKenzie and Woodruff (2008, 2009) and Karlan et al. (2014), suggest credit or insurance market failures can limit investment in productive activities. Failures in the credit market in turn may result from asymmetric information and commitment constraints, or lack of effective competition and sub-optimal screening policies by suppliers (Karlan and Zinman, 2009, Jack et al., 2017). But even when poor people in the developing world have access to credit, especially through microfinance institutions, the impacts appear to be limited. A collection of six randomized evaluations of microcredit programs (Banerjee et al., Tarozzi et al., Attanasio et al., Crepon et al., Angelucci et al., and Augsberg et al., 2015), as summarized by Banerjee et al. (2015), confirmed "modestly positive, but not transformative, effects." In a different study, Crepon et al. (2013) find that access to credit shifted the source of income from labor earnings to business profits, but with little impact on total income or consumption.

In summary, despite the vibrant literature on traditional credit and microcredit and its impacts, there is no evidence on the impact of digital credit products like M-Shwari, which are relatively new but growing in importance, especially with the expansion of so-called "fintech" services. Subject to whatever borrowing limit that is placed on borrowers through the credit-scoring algorithm, access to credit is, in principle, more immediate and more private than traditional microfinance delivery mechanisms. Our paper is the first to document how individuals respond to this kind of credit access.

II. Background on M-Shwari

The growth of mobile money in Kenya has prompted a large response from private sector banks to build credit products over the rails of mobile money. One very successful product that has been launched is in Kenya, called M-Shwari, a fully digital bank account offered by the Commercial Bank of Africa (CBA), with remunerated savings and credit services. The account is linked to M-PESA, the popular mobile money service in Kenya, provided by the mobile network operator, Safaricom, and is opened and operated through a USSD application on an account holder's phone. Loans are dispensed into users' mobile money accounts and the money can be transferred into and out of their M-Shwari accounts (without cost). The withdrawals and deposits out of M-Shwari accounts use the existing mobile money infrastructure in the country. M-Shwari offers both a savings account (as well as a lock box savings account) and the opportunity to get short term loans.

M-Shwari has been an important source of competitive advantage for CBA in the banking industry in Kenya. It has grown their market share dramatically and has been an important source of revenue for them. M-Shwari has transformed the banking industry in Kenya, with competitors now providing similar products (though their take up is still low). In Figure 1A, we show how M-Shwari has changed CBA's place in the banking industry between 2010 and 2017 (remember M-Shwari was launched in late 2012). CBA's market share in the number of deposit accounts and the number of loan accounts has grown tremedously and, as can be seen, from this figure, it all comes from an expansion in the number of small value deposit accounts, i.e. M-Shwari.

The loans disbursed by M-Shwari are uncollateralized and start off at rather small amounts, with the first loan often as low as KSh 100 (one US dollar) but sometimes as high as KSh 10,000. Over time, even if an individual starts off with a low credit limit, if they repay and save, they can grow their limit. Each loan has to be repaid within 30 days and is charged a 7.5% facilitation fee. Behind the loan approval process is a set of credit approval and scoring rules based on data on the user's M-PESA record (they have to have been an active M-PESA used for at least 6 months and use other Safaricom products like voice, data and M-PESA). The credit scoring process gives individuals a loan limit which increases upon the timely repayment of a loan. If a loan is not paid on time, the loan is extended for another 30 days with a 7.5% facilitation fee charged on the outstanding balance. After 120 days of non-payment, the borrower is reported to the credit reference bureau. Note that any prepaid airtime on the user's phone and M-PESA balance cannot be used to clear loans (unless the M-PESA balance is moved to M-Shwari as savings by the user). However, savings in M-Shwari can be reclaimed towards the loan (though the savings are never locked for the duration of the loan).

M-Shwari assigns customers a credit score as soon as they sign up for an account, irrespective of when they choose to borrow. Customers are not informed of their score but are assigned a first credit limit (that is based on the underlying score). The formula for the credit limits is separate from that determining the original credit scores. For customers with scores below the cutoff for being approved for a loan, they are assigned a zero credit limit. Over time, those with zero credit limits can have their limits upgraded by saving in their M-Shwari accounts. We describe these credit limits and their evolution in more detail in the next section.

On the savings side, M-Shwari pays interest that accrues daily but only paid out quarterly. During the period of this study the annual interest rates were 2% for balances between KSh 1 and KSh 10,000, 3% for balances up to KSh 20,000, 4% for balances up to KShs 50,000 and then 5% for balances above KSh 50,000. This study focuses on evaluating only the credit component of M-Shwari since the research design is based on using the credit score in an RD framework.

III. Data

For this study, we use three different datasets. First, we use administrative data from the bank for customers that opened their accounts between January and March 2015. The data was pulled in July 2016, so approximately 18 months after these customers opened their accounts. Second, we collect survey data on a sample of these customers. We use the administrative data to draw a sample of 6,000 individuals to survey. Third, we recently received administrative data on a random sample of 10,000 M-Shwari customers who opened their accounts between January and March 2016 where we can follow the entire evolution of their loan histories and credit limits. We do not have this data for the original survey sample as the bank had concerns about how we may use these data given we can match it to a wide range of individual characteristics in the survey and potentially create better credit scores ourselves. In this secton, we describe each of these three datasets in detail.

To design the study, we used the first round of administrative data from the bank to conduct power calculations and to decide the credit score bandwidth that we would sample M-Shwari clients from. We computed the optimal RD bandwidth using this administrative data for the outcomes of loan take up and the number of loans. This optimal bandwidth was 10 credit score points on either side of the cutoff. We therefore designed our final survey sample to have credit scores in the range of -9 to 10 (covering 10 units of the credit score below the cutoff and ten above). The administrative data covered a little over 1.1 million total clients, with about 156,000 falling in the chosen bandwidth. For this sample, we know their credit score, whether they took out a loan and the total number and quantity of loans they took out on M-Shwari over th 18 months since they opened their accounts. We do not know the full evolution of their loans or credit histories.

To operationalize a study sample, we asked the bank to draw a random sample of 6,000 clients who opened up an M-Shwari account between January and March, 2015 and whose credit scores lay between -9 and 10. For 5,000 of these 6,000 clients, we have administrative data on their credit scores, the underlying M-PESA data that was used to create these credit scores and some aspects of their loan history with M-Shwari.[8]

We then attempted to survey these 6,000 individuals. The surveys were all conducted by phone (the bank operating M-Shwari does not know the location of their clients) and were conducted between September 2016 and January 2017, more than a year and a half after these individuals opened their M-Shwari accounts. Tables 1 A-C report some of the basic characteristics of our sample. Tables 1A and 1B show the summary statistics for our overall sample, and Table 1C shows the summary statistics, splitting the sample into "treatment" (i.e. people who were just eligible for the M-Shwari loans) and "control" (i.e. those with credit scores just below the cutoff who are ineligible for the loans).

In terms of demographics, Table 1A shows that the average person in our sample is 30 years old and the sample seems balanced on gender (48% male). With regards to cell phone usage covering the 6 months prior to opening an M-Shwari account, Table 1A shows that the average customer has total M-PESA transactions of around 4000 KSh (approximately $40), has used a prepaid airtime loan product given by Safaricom (called *Okoa Jahazi*) about 17 times, and spends about 4,700 KSh in prepaid airtime top up amounts. Consistent with the fact that our sample is drawn from a poorer portion of the overall population (since our sample is restricted to individuals near the credit score threshold), Table 1A shows that on average, people in our sample

[8]We only have administrative data on 5,000 clients as the Bank first sampled 5,000 for us randomly from those that opened an account in this time window. Given the survey non-response rates, we asked the bank to then sample an additional 1,000 clients, but they did not provide us with administrative data aside from the credit score and phone numbers for these 1,000.

experience 103 “low days”, which is the number of days the customer has had less than 2 KSh (USD 0.02) of airtime balance. Individuals in our sample on average have 3 unique entities to whom MPESA transactions are made, make about 2.9 paybill payments (to about 0.4 unique paybill clients), and transfer money from 0.18 bank accounts in the 6 month period prior to opening an M-Shwari account.

Table 1B shows summary statistics from our survey sample. The average customer lives in a household with 4.4 members and where the head of the household has approximately 10.8 years of education. This table shows that over 82% of households in the sample had some positive savings in the previous month (note that however only 65% had positive savings accounts balances at the time of the survey), and the average amount of savings in these households was around 7512 KSh (the average current savings balance was around 7,743 KSh). While large fractions of households in the sample (perhaps predictably) spend positive amounts on things such as education, clothing, and medical expenses, perhaps more remarkably, households also face a high likelihood of having negative shocks. Nearly 90% of households report having experienced some negative shock in the 6 months prior to the survey date. A negative shock in this case comes from the survey question that asks households about unexpected events they experienced, including the death of a household member, the illness of household member, accidental injury, the loss of employment, violent injury, the failure/loss of business, livestock death, crop disease /pests, theft/robbery/burglary/assault, fire/house destroyed/damaged, and drought/floods. Over 41% of households report missing a meal in response to these shocks. A similar fraction of households also respond to shocks by removing a child from school or reducing non-food expenditures.

Table 1C shows a selection of the variables in Tables 1A and B, but split into “treatment” and “control” groups, where treatment simply means individuals with a credit score above the cutoff making them eligible for M-Shwari loans. At first glance, Table 1C shows that individuals in the treatment group have more outstanding loans, have higher levels of debt, and are more likely to have an M-Shwari loan (34% vs 21%). Note that the non-zero (21%) share of the control group with M-Shwari loans arises because our credit score cut-off is recorded at the time of account opening, while loan eligibility itself can evolve over time.

An important concern when implementing an RD design is manipulation of the running variable. The chances that individuals can manipulate whether they fall on one side of the M-Shwari eligibility threshold is unlikely since the credit score is a complex formula using individuals' mobile phone and M-PESA data. Figure 1B shows the distribution of credit scores around the credit score cutoff in our sample of 6,000 individuals. As we mentioned above, we only drew a survey sample in a narrow window of credit scores, ranging from -9 to 10. It is important to note that at least visually, there appears to be no evidence of systematic manipulation of the credit score variable which would result in heaping around the cutoff.

Figure 1C shows where in the overall distribution of credit scores our sample is drawn from using the same administrative data we intitally drew the survey sample from. Figure 1C shows that the RD sample credit scores are drawn from the middle of the credit score distribution and comprise about 15% of the overall sample of credit scores (i.e. the universe of credit scores for customers who opened their accounts in the January to March 2015 window). Finally, it is worth discussing response rates to the phone survey. While survey response rates are rather high (from a sample of 6,000, we were able to reach 4,136 households, i.e. a 69% completion rate), it is also important that we find that the non-response is not differential across the cutoff (something we return to in Table 2B). It is not the case that people who just qualified for the loan were more or less likely to respond to the survey, relative to people who just missed being qualified.

In order to learn more about the evolution of loan amounts and limits, we obtained data from the bank on a completely different sample of individuals. For reasons described above, the bank preferred to give us subsets of outcome data on different individuals than the universe of outcomes for the same individuals. Hence, in order to learn about loan limits and the evolution of loans for individuals, we obtained a sample of about 10,000 individuals who opened their accounts between January-March 2016 (about one year after our study sample opened their accounts). This sample is for all credit scores. Of these 10,000, there are 1,468 in our RD window (approximately 15% of the full sample), and we have data for individuals up to September 2016, approximately 7-9 months after they open their accounts.[9] Table 1D contains the summary statistics on this separate sample and shows that the overall loan amount taken over this period is around 8,200 KSh which is more than two and a half times the total loan amount taken by individuals within the RD bandwidth (around 3,200 KSh).

Figure 1D shows the evolution of number of loans taken by individuals above and below the RD cutoff. Each black dot therefore represents the average number of loans taken by people above the cutoff (between a credit score of 1 and 10) at a given date since January 1, 2016. Similarly, a grey dot represents number of loans taken by people below the cutoff (between a credit score of -9 and 0) on a given date. The important thing to notice about Figure 1D is that people below the cutoff do not take out loans in January or February (i.e. right after they open their accounts), which is consistent with the story that it takes these individuals below the cutoff some time to improve their credit limit and become eligible for loans. Also, the bank does not update credit limits in real time or daily. Moreover, Figure 1D shows that over the following few months, those above the cutoff in January through March are consistently taking out more loans than those below the cutoff. That is, while those below the cutoff start accessing loans, they are unable to fully catch up in terms of number of loans at a given point in time.

Figure 1E provides details on the evolution of credit limits (recall that the previous figure was about loan amounts) above and below the cutoff. Consistent with the above, credit limits are positive for those individuals above the cutoff immediately after they open their accounts (i.e. within the January to March 2016 window), but evolve more slowly for those who are initially below the cutoff. It is not until in April 2016 that we see positive credit limits emerge for those below the cutoff. However, for those who make it past the threshold, the credit limits become quite similar to those who were already above the limit, suggesting that at least within a short window, those above and below are likely engaging in very similar behavior in terms of what matters for improving their credit limits. Finally, in Figure 1F we see that nearly all loans that are taken out within our RD bandwidth are taken at the credit limit. In other words, there

[9] The cutoff for loan eligibility did not change between the start of our original sample and this newer sample and neither did the credit score formula.

are very few loans where the loan size is below the credit limit.

IV. Methodology

Here, we briefly describe the RD design we are using. Given the cutoff used to determine loan eligibility, we follow the standard RD design framework and estimate the following equation:

$$Y_i = \alpha + \beta D_i + \gamma_1 (X_i - c) + \gamma_2 (X_i - c) * D_i + \epsilon_i \tag{1}$$

where Y_i is an outcome for individual i, and D_i is an indicator variable for whether the individual qualifies for the loan by being above the credit score cutoff, c, and X_i represents the individual's actual credit score. Hence, γ_1 and γ_2 flexibly capture the direct effect of the "running variable" (in this instance the credit score) on the outcome of interest. Given these controls, β captures the effect of being just above the cutoff to being just below the cutoff, or the treatment effect of interest to us. In all the results, we only report the β coefficient. This is the local linear specification commonly used in RD designs and our main regressions show results using the optimal bandwidth we used to sample, as described above, as well as half this optimal bandwidth (the latter for robustness).

Aside from this standard specification across all outcomes, we also conduct a number of robustness checks. First, we vary the bandwidth of the estimating equation to show that our results are robust to a wide range of bandwidths. Second, we check whether a set of pre-determined variables are discontinuous around the cutoff (i.e. the same specification as the equation above) to see whether individuals on the left and right of the cutoff have statistically different characteristics. We find no evidence of such discontinuities.

V. Results

V.1 Balance of covariates

We first show that any pre-determined characteristics in the sample are continuous through the cutoff. The results are reported Tables 2A and 2B. Put together, Tables 2A and 2B give us confidence in the idea that the people right around the cutoff are very similar except for qualifying for loans on M-Shwari.

In Table 2A, we show results for variables only from the administrative data, in particular, both characteristics of the user as well as variables on their interactions with Safaricom and M-PESA (variables that ultimately enter the credit score). For all these variables, it is clear that they do not change discontinuously around the cutoff, lending support to our empirical strategy. Columns (1) and (2) report results for the age and gender of the customer. Columns (3) through (5) report results for variables related to Safaricom prepaid (98% of the market in Kenya is prepaid) airtime use by the individual over the six months prior to the individual opening their M-Shwari account. "Top up" is the amount of airtime purchased, "Number of loans" is the number of times they have taken out an airtime loan and "Low days" is the number of days the customer has had less than 2 Kenyan shillings (USD 0.02) of airtime balance on their account. Columns (6) through (12) show results for variables related to the individual's M-PESA record for the six months prior to them joining M-Shwari. In particular, "Value" is the value of total inflows (money received plus deposits made plus any bank transfers), "1m/6m Bal" is the average daily balance in the person's account in the past 1 month/6 months, "Send" is the number of unique individuals money is sent to via MPESA, "Paybill" is the number of paybill payments made over M-PESA, "Paybill clients" is the number of unique paybill payments made (the number of unique organizations the individual has paid on M-PESA using the paybill service), and "Bank clients" is the number of unique bank accounts that the customer transferred money from. Across all these variables in Table 2A, we find no evidence of a discontinuous jump at the credit score cutoff.

In Table 2B, given the discussion above, we look at non-response in the phone survey as well as any pre-determined characteristics where we would expect balance. Survey non-response is reported in column (1) of Table 2B. As can be seen here, there is no differential non-response on either side of the cutoff. We are therefore less concerned about non-response affecting our results. In the rest of Table 2B, we draw on the survey we conducted and look at some variables from the survey that are arguably pre-determined and therefore unlikely to be affected by the loan (recall that M-Shwari loans are quite small, approximately KSh 554, or 5.5 USD in size so we do not expect them to affect assets like land).

In columns (2) through (5), we first look at a number of measures of the demographic status of the household that the individual in the sample belongs to, in particular household size, the number of girls in the household, the number of boys in the household and the number of adults. Across these columns, we find no evidence that demographics are different around the cutoff. In columns (7) through (12) we look at a number of individual and household characteristics that are pre-determined and though we find no evidence of a discontinuous change in any of these variables around the cutoff. In particular, we show this for the age of the individual, whether the individual is Catholic, the education of the household head, the education of the spouse of the household head, the number of acres of urban land owned, the number of acres of rural land owned and whether the household has moved in the last year.

V.2 Outcomes

Next, we look at outcomes.[10] We first start with the set of outcomes that we refer to as "first stage" outcomes. These are the outcomes that focus on the first target of the M-Shwari product: loans. We therefore look at a number of different first stage outcomes in Table 3, some of which we also show in Figures 2A and 2B.

Figure 2A uses administrative data that spans 18 months after individuals open their M-Shwari account. Note that these graphs use the full sample of M-Shwari clients (not the subsample around the cutoff for whom we have survey data), and also spans a much larger bandwidth

[10]We do not show any outcomes by gender. There are no differential impacts based on gender of the respondent. Results available upon request.

compared to what we use for the rest of the paper. Figure 2A shows in striking clarity the first stage of our design – individuals whose credit scores fell above the cutoff are significantly more likely to have taken a loan, have more total loans, and have higher loan amounts.

Figure 2B shows graphical evidence using survey data (and hence a much smaller bandwidth and fewer individuals) that having access to M-Shwari loans leads to higher take up of credit from *any* source. This graph shows that the difference in the likelihood of having any kind of loan between people just below and just above the cutoff is around 11 percentage points, which is slightly smaller than what we observe in the administrative data, suggesting that there might be some measurement error in the survey data relative to the administrative data. It is important to note that people just below the credit score threshold also have loans - indeed the mean here appears to be around 46%.[11] Hence, the digital loan program we evaluate in this paper should be understood to affect households by expanding access to credit, not by introducing it from a zero base. Indeed, the last panel in Figure 2 also shows this fact – when examining total household debt, it seems like being above the cutoff increases the debt held (similarly the middle panel of Figure 2 shows similar results for the total number of loans).

Tables 3 onwards show the regression analogs of the Figures, estimated according to equation (1) above. We also present these results for two sets of bandwidths to show that our results are not driven by choice of bandwidth. While the tables all show coefficients and standard errors, we also often show p-values that adjust for multiple hypothesis testing (as per the Sidak-Holm adjustment).

Table 3A shows the regression analog of Figure 2A (using the administrative data), but estimated over the same sample for whom we have survey data. Column (1) in Table 3A shows that those above the cutoff are 24 percentage points more likely to have a loan (off a base of nearly 30 percent). Those above the cutoff are also more likely to have more loans overall (1.3 more loans off a base of 1.9 loans), and have nearly a 1,000KSh more in total loan amounts (the average in the control group is 1,500KSh, se see Column (3)). In line with the idea that those with higher

[11]Note this survey question is about *any loan*, not specifically M-Shwari loans; the mean of M-Shwari loans in the control in our survey is around 20% which is comparable to what we see in the administrative data.

scores have higher credit limits, the average loan amounts borrowed by individuals above the cutoff is nearly twice that of those below the cutoff (see Column (5)). Column (7) shows an important result that people on either side of the cutoff are no different when it comes to default probabilities on the first loan. This also serves as an important check on the RD design, which relies on the idea that those on either side of the cutoff are largely similar in terms of underlying characteristics such as the ability to repay loans, etc.

Table 3B shows the regression analogs of the graphs in Figure 2B (using our survey data). This table shows that individuals with credit scores above the cutoff are more likely to take up any loans (column (1)), as well as have more loans (column (2)) and more total debt though this is noisily estimated (column (3)), probably because the amount loaned by M-Shwari is ultimately small. The magnitudes from this table's columns (1) and (2) mirror the magnitudes in the graphical analysis: column (1) shows that people just above the cutoff are 10.6 percentage points more likely to hold any loan. Since the approximately 46% of people in the control group hold any loans (the table shows the control means), being just above the cutoff results in a substantial increase in the probability of holding any loans.

In column (4) we look at a log transform of the total amount of debt held since many individuals hold zero debt, and this column shows a significant increase in the debt held by households. While this result appears to be sensitive to choice of bandwidth, the coefficients are not statistically distinguishable from each other. In column (5) we look at total formal debt (defined as debt from M-Shwari, other banks, MFIs, savings and credit cooperatives or SACCOs, and rotating savings and credit associations or ROSCAs). While not statistically significant, these results show a meaningful increase in overall formal debt held by households. Finally, to address any concerns that small digital loans may needlessly put people in debt, or become a financial burden through high interest payments, in column (6), we examine total interest paid on all loans (as a fraction of household daily consumption). Column (6) shows no differential interest burden due to M-Shwari. Column (7) shows that those likely to access loans are not more likely to turn around and loan to others.

An important robustness check in RD designs is to show that the choice of the bandwidth within a reasonable range does not significantly alter the results. While Table 3B itself shows results for two different potential bandwidths, we show more bandwidths in graphical form in Figure 4. This figure shows that the RD estimate of interest (the β coefficient) on whether being above the cutoff leads to holding more loans does not change appreciably when we incrementally start reducing the bandwidth from full (-9 to 10) to -8 to 9, -7 to 8, and so on, until -4 to 5. The stability of the coefficients across the bandwidths provides strong support to the proposition that our results are not being driven by an arbitrary choice of bandwidth around the cutoff.

Table 3C takes a more detailed look at the different types of loans to analyze whether access to short-term loans from M-Shwari leads individuals to substitute away from other sources of credit. This is important since we argue that access to M-Shwari leads to an overall expansion in the access to credit, rather than just a substitution of credit from one form to another (substitution to other credit forms is well studied in the context of payday loan regulation - see Bhutta, Goldin, and Homanoff 2016 for example). Columns (1)-(5) examine formal sources of credit and it is clear when we compare column (1) to columns (2)-(5) that all the increase in loans that we saw in Table 3B is the result of M-Shwari. Columns (2)-(5) show that there are no effects (statistically as well as in magnitude) on other forms of formal credit, be they from ROSCAs, SACCOs, other MFIs or banks. Note that these other forms of credit have very low take up to begin with. Column (6) examines informal loans (from moneylenders, friends, family, employers, employees, and church or religious groups) and finds small and insignificant impacts on this type of loan too. Hence, it is likely that access to M-Shwari loans, which have a control group mean of 21%, is an important channel for increasing overall access to credit for this group of individuals.

Given the size and short-term nature of these loans, the next outcome we examine is whether these loans help households be more resilient when faced with shocks. In Table 4A we report results for these outcomes. Column (1) first examines whether households above the threshold are more likely to experience negative shocks. Not only is the coefficient in column (1) statistically insignificant, compared to the mean, it is economicalIy not meaningful. In column (2), we use an aggregated measure of whether a household reported having to forego any expenses in responses to a shock (hence we do not report a Sidak-Holm p-value for this column since it is already an aggregated measure). In columns (3) through (5), we look at whether households reduced expenditures in certain budget categories in response to negative shocks. As the results show, households with individuals above the cutoff are less likely to report that any expenses were foregone (shown in column (2) and graphically this is seen in Figure 3) and medical expenses (column (4)). These loans are therefore useful for mitigating the effects of shocks. Note the high mean in the control group: approximately 68% of households in the full survey sample, in general, forego expenses in response to a shock. However, households with individuals above the M-Shwari loan cutoff are 6.3 percentage points less likely to report foregone expenses, which relative to the mean, represents a 9% effect. In columns (6) though (8) of Table 4 we look at other adjustments households may have made in response to negative shocks, in particular whether they removed a child from school, whether they left a job or whether they sold any assets. Across all these three measures, we find no statistically significant effects of the M-Shwari loan.

In Table 4B, we look at whether M-Shwari provides households with resilience to particular types of shocks since we know from our surveys exactyl what the shocks were. To do this, we interact each type of shock separately with the cutoff (while controlling for the main effects of the cutoff and the shock). Therefore, the interaction term (Cutoff X Shock) illustrates whether households above the cutoff are *less likely* to forego expenses in response to a specific shock (which appears as the column title for each regression). The regressions still condition on the sample that has negative shocks like in Table 4A, so these simply illustrate whether M-Shwari loans provide better protection for some shocks against others. In line with Table 4A, the main effects of the score are all negative and significant (both statistically and economically). Given the relevant interactions, it seems like M-Shwari helps particularly for health shocks (column (2)) and if there is a death in the household (column (5)). This seems intuitive as these shocks are typically unexpected and result in significant immediate expenditures.

Table 5 examines daily per capita consumption along a large set of measures for members of the M-Shwari account holder's household, conditional on the household having faced a negative shock in the past 6 months. Note that in this table while we show the p-values for multiple hypothesis testing, we do not expect all categories of consumption to respond to M-Shwari loans. Since we have no priors on what categories should respond and what categories should not, it is not clear that there is much to be made of multiple testing. Yet, for completeness and for readers who wish to interpret these results as being a culmination of null results, we report p-values that do adjust for multiple hypothesis testing. The first four columns examine total expenditures, food expenditures, expenditures on basics[12] and expenditures on prepaid airtime for mobile phones. Not only are the coefficients for these four columns statistically insignificant, their magnitudes are small. The remaining columns examine whether a household is likely to report positive expenses along a range of outcomes. While we find no impacts on health (column (6)), clothing (column (7)), assets (column (8)), temptation good[13] expenditures (column (9)) and alcohol and cigarettes (columns (10)), we find a large and marginally statistically significant impact on education expenses (column (4)).

Households just above the cutoff are 5.8 percentage points more likely to report positive expenditure on education compared to households just below the cutoff (on average, 77% of households in the control report positive education expenses). In the smaller bandwidth, the effect is 5.9 percentage points (with a control mean of 77%). These results are shown graphically in Figure 3 (with robustness across bandwidths shown in the third panel of Figure 4). Although this may seem surprising at first, looking at the data, households report spending the loan, quite often, on emergencies, especially health events. However, even though households spend the actual loan money on, say, medication, the marginal dollar from the loan gets spent on the item they would have adjusted had they not had access to the loan. This happens to be education, a result that is consistent with Jack and Suri (2014) and Suri et al (2012) who find similar effects when studying how M-PESA affects consumption smoothing.

Finally, Table 6 examines whether increased access to loans affects the financial and real

[12]We define basics as including expenditures on water, rent, electricity, any form of firewood, fuel, gas and electricity.

[13]We define temptation goods as including food consumed outside the household (whether purchased by the household or gifted), and alcohol and tobacco expenditures (both own expenditures as well as gifts).

assets of the household to which the M-Shwari loan-eligible individual belonged. We find that such households do not seem to have increased savings along any of these measures. This is not that surprising given these are short run loans and intended either for emergency purposes or for working capital in informal micro enterprises. Moreover, the amount of the loan is likely small in comparison to the average savings in a household. In column (1), we report the effect of the loan on the number of instruments used by the household to save – this increases by 0.18 and may well correspond to individuals using their M-Shwari accounts to save; hence, this is a rather mechanical result. Looking at whether these households had any savings last month and the amount (columns (2) and (3)) we find no evidence that M-Shwari had an impact. In columns (4) through (7) we look at the self-reported current savings balance, again looking at whether the household had any savings balance (column (4)), the total amount saved (column (5)) as well as the total value of assets (column (6)) and the value of productive assets[14] (column (7)). We find no effects of eligibility for an M-Shwari loan on these measures of household savings.[15] Neither do we find any effects of savings in M-Shwari accounts themselves (results not shown).

VI. Conclusion

Overall, our results suggest that loans from M-Shwari have high take up rates among those who are eligible for them, and that they have salient impacts on mitigating shocks. The results confirm that these short term digital loans are largely used to pay for schooling and for emergency purposes and not for business or working capital purposes, at least in the sample of customers we study within the somewhat narrow window of credit scores around the cut-off. Hence, our results, like standard RD results, need to be interpreted as relevant to the local bandwidth that is examined. Given the size and short-term nature of these loans, we find no impacts on other measures of welfare like assets, wealth, or consumption. This is all the more salient given the surveys were conducted starting in September 2016, which was at least eighteen months after

[14]We define productive assets as including phones and accessories, livestock, computers and all types of vehicles.

[15]We acknowledge that savings are self-reported and are subject to considerable measurement error. However, our survey questionnaire on this follows the best practices in the literature till date.

these individuals opened accounts on M-Shwari (note that the long term impacts in Suri and Jack (2016) were after eight years of access to M-PESA). Hence, although these are not truly long term effects, they are also not short term effects. In relation to Suri and Jack (2014), the improvements in resilience we see are similar to what the authors find for M-PESA but with the big difference that M-Shwari is a short term loan that has to be paid back rather soon. Moreover, remittances examined in Jack and Suri (2014) are informal, and repayment depends on the risk sharing agreements between individuals.

A valid concern at the outset of M-Shwari's loan product roll out was that it would simply act as a substitute for other loan sources and that this might not increase the total amount of credit to which households have access. Our results suggest that M-Shwari does indeed expand the envelope and access to overall credit (since we find significant impacts on the total number of loans held by households), and the magnitude of this impact on the total amount of loans is significant.

Did digital loans deliver? In conclusion, our results show that small loans that are quickly delivered via mobile technology have high take up (34% of those eligible take up this product, and on average within eighteen months, individuals take up six such loans) and can help households not have to forego expenses due to shocks. Digital platforms for loan delivery seem to be able to overcome some of the costs associated with traditional forms of credit access and repayment, and hence, seem to have some measure of success for both financial entities and clients in this context. Certainly, these small, short-term loans cannot be expected to be transformative in the sense of improving asset holdings, or helping jump start entrepreneurship among individuals. Whether this delivery mechanism can help with the take up, delivery, and repayment of larger loans or loans targeted for specific productive purposes (i.e. those that could be "transformative") is a crucial next step for research in this area.

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Figure 1A: CBA Market Share, 2010-2017

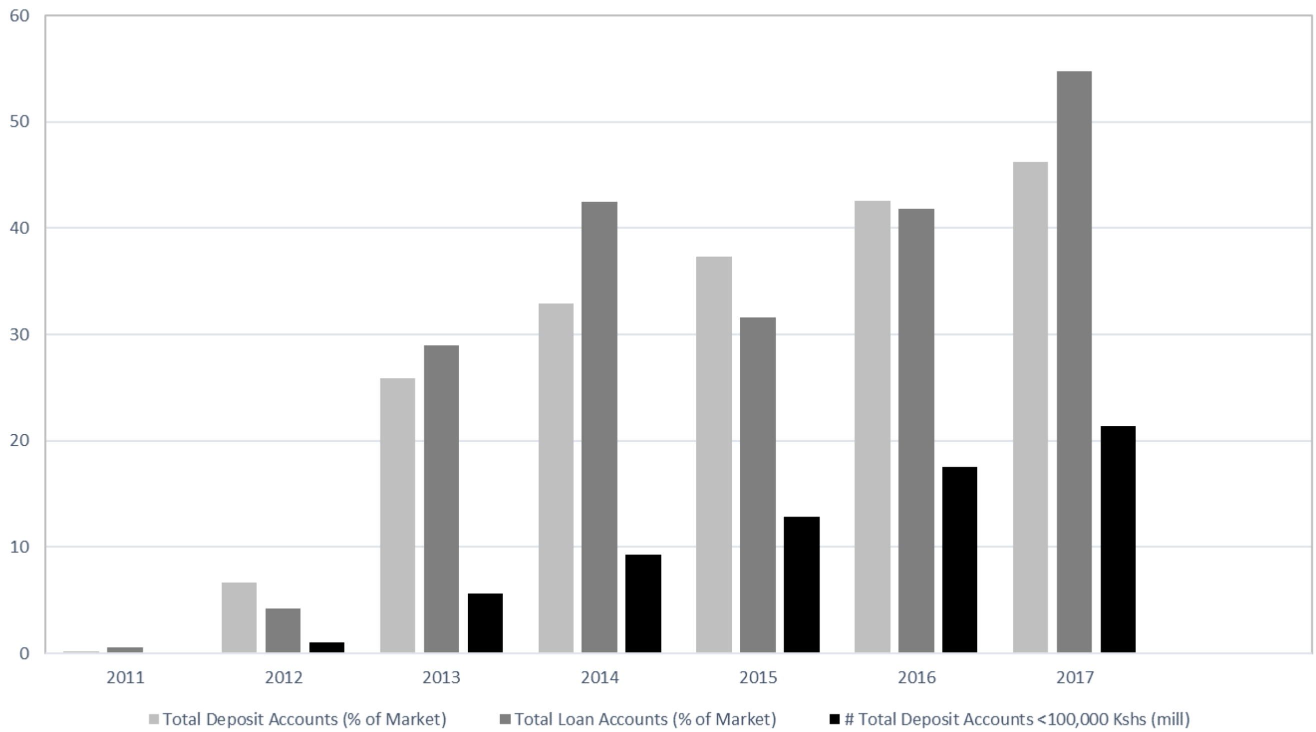
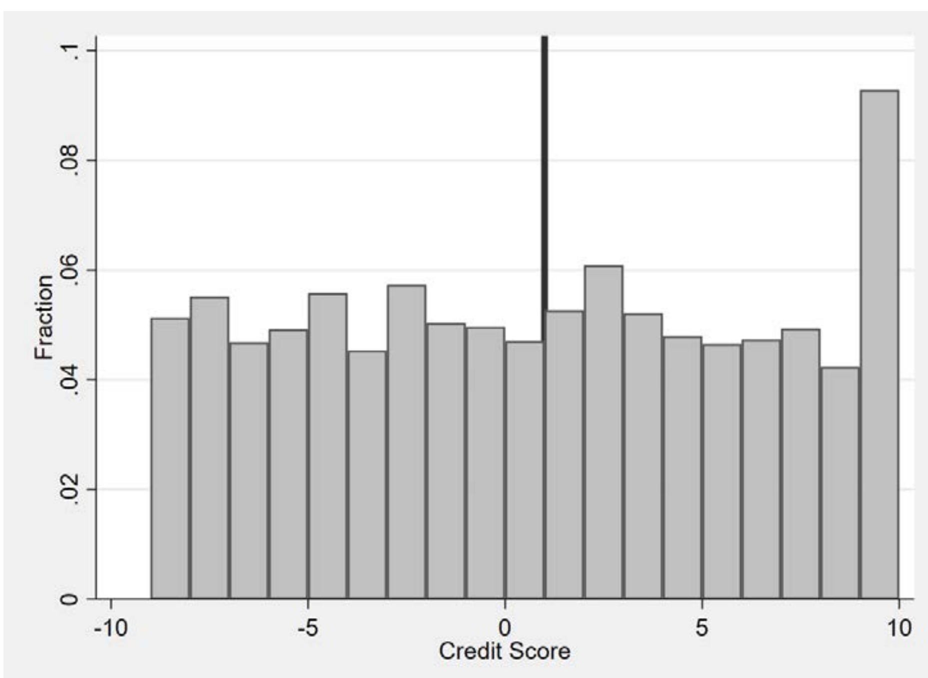
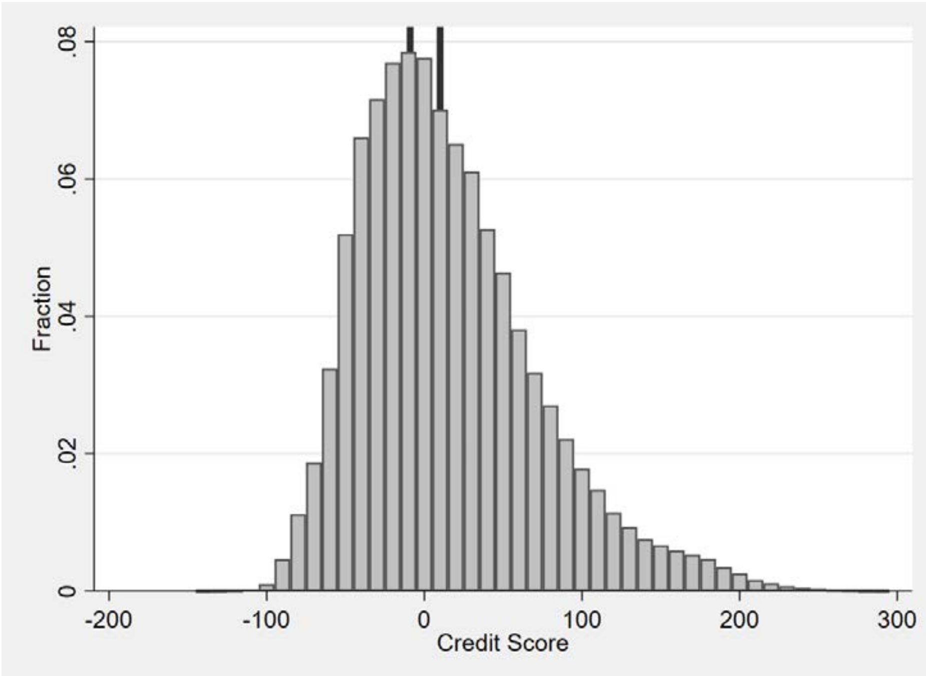


Figure 1B: Histogram of Credit Score



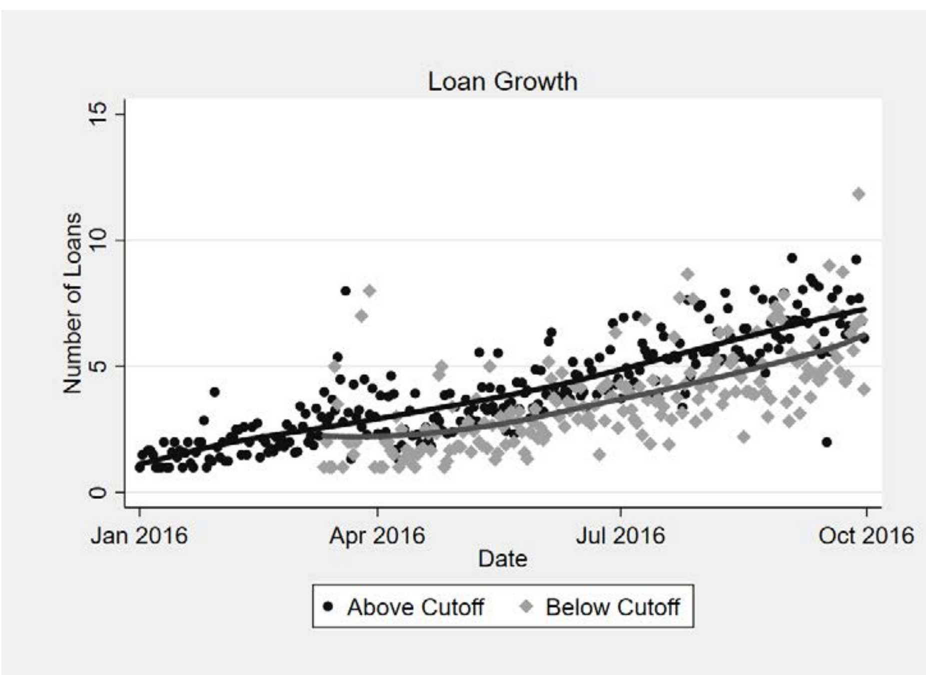
Note: The survey sample was drawn from M-Shwari customers with credit scores spanning -9 to 10.
Individuals were assigned a credit score (that never changes) at the time of account opening.
Individuals with a credit score strictly above zero were eligible for loans of varying sizes (depending on the score).

Figure 1C: Credit Score Distribution



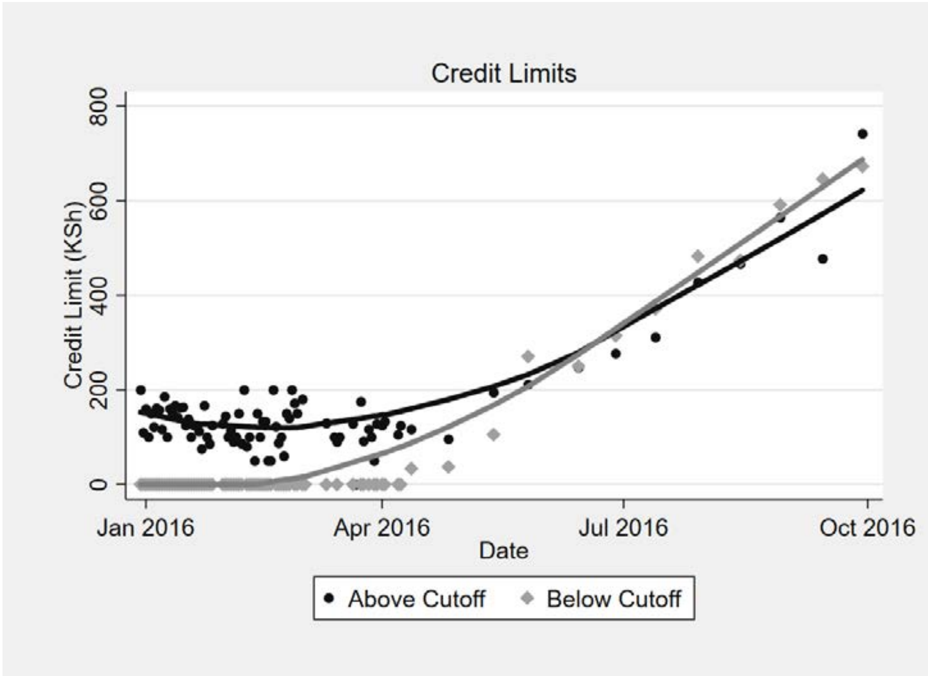
Note: The RD window is marked in black and covers 15% of the overall sample of accounts.

Figure 1D: Loan History (Separate Sample, RD Bandwidth)



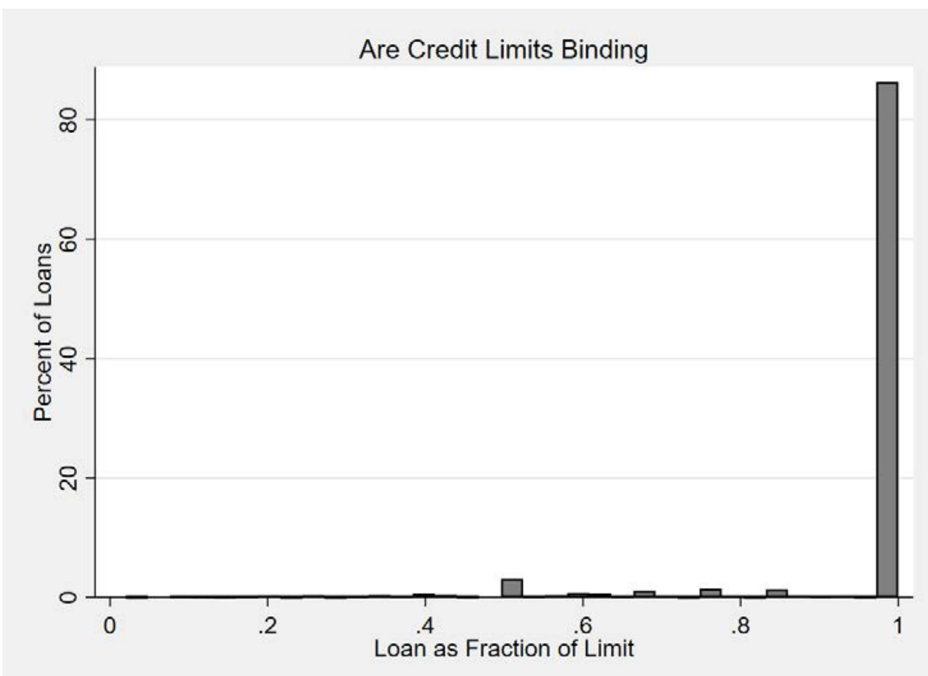
Note: The survey sample was drawn from M-Shwari customers with credit scores spanning -9 to 10.
This graph is from a different sample of M-Shwari customers than the study sample (see text for details).
Individuals in this sampled opened accounts in January 2016 and the data runs till the end of March 2017.

Figure 1E: Credit Limit Evolution (Separate Sample, RD Bandwidth)



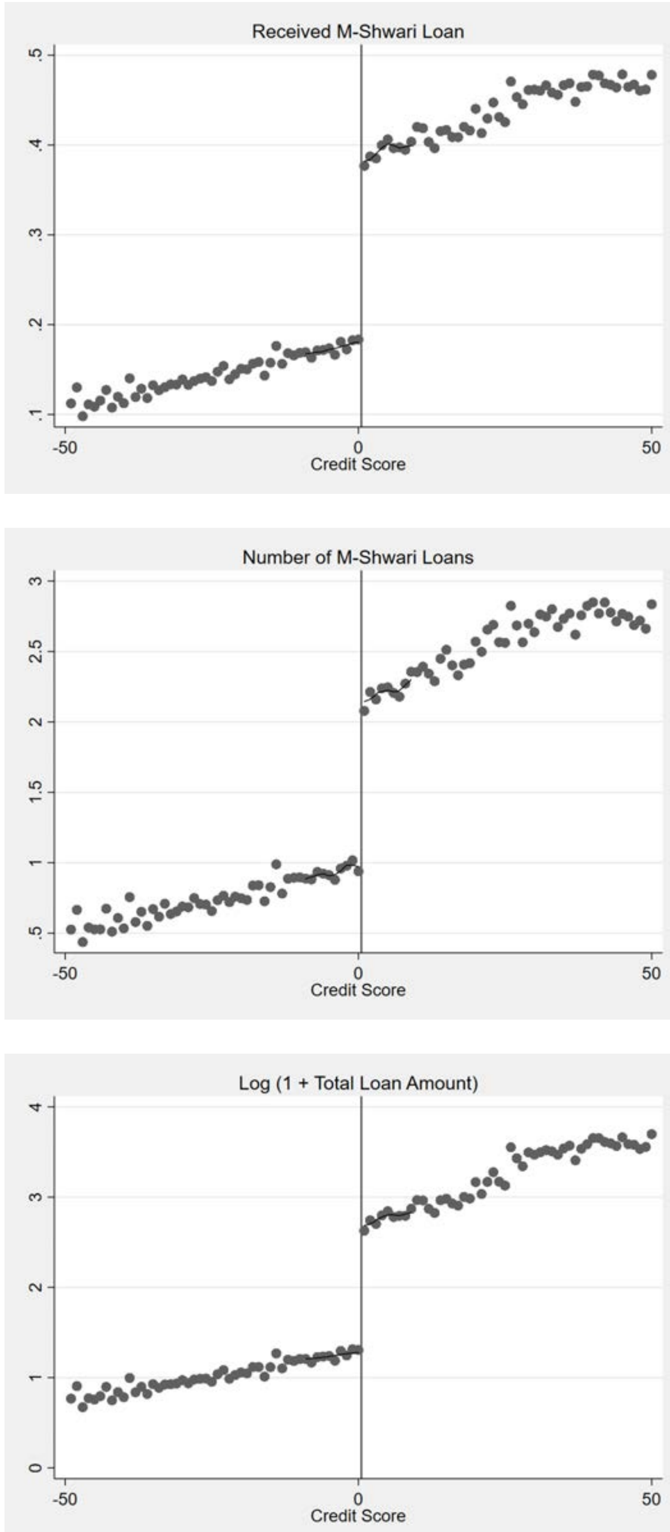
Note: This is from a different sample of M-Shwari customers than the study sample (see text for details). Credit limits are reported in Kenyan shillings (KSh). The exchange rate is KSh 100 to the dollar.

Figure 1F: Loans and Credit Limits (Separate Sample, RD Bandwidth)



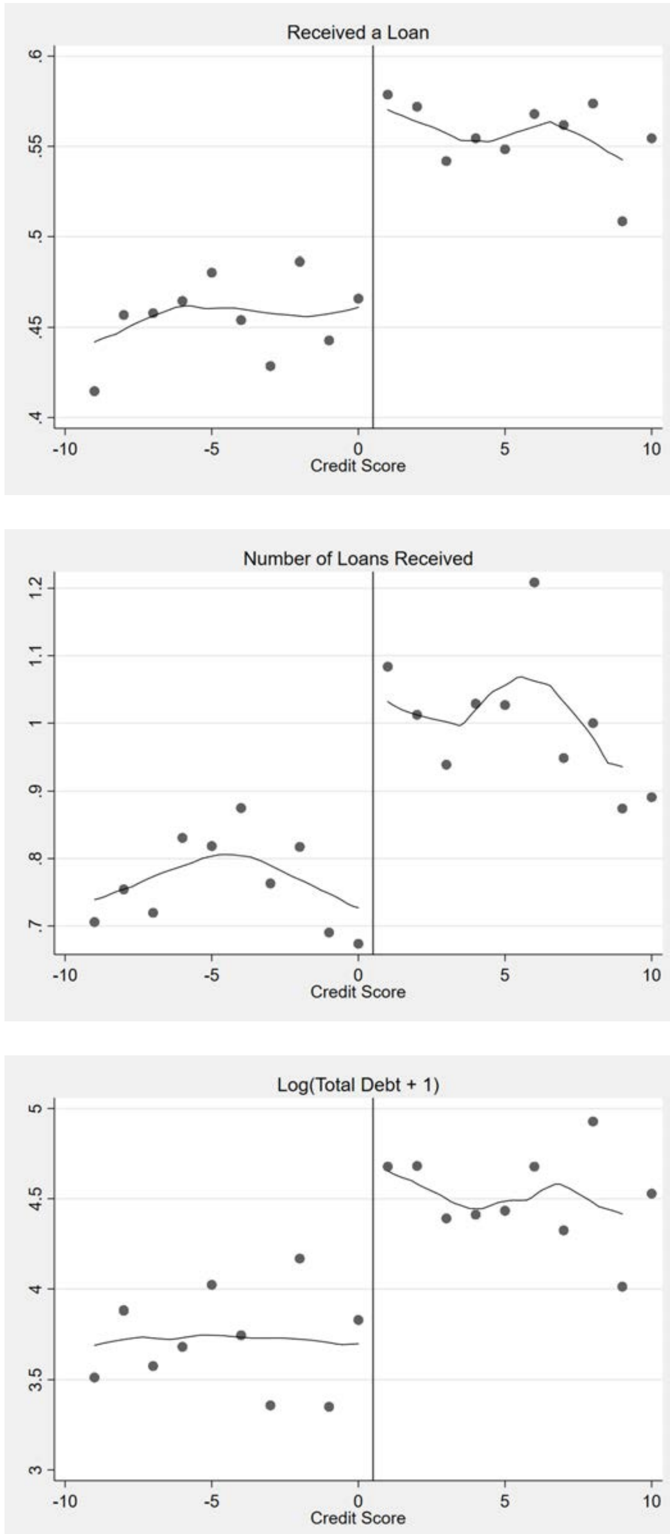
Note: This is from a different sample of M-Shwari customers than the study sample (see text for details). This figure uses daily loan level data (conditional o borrowing) for this sample.

Figure 2A: First Stage, Administrative Data



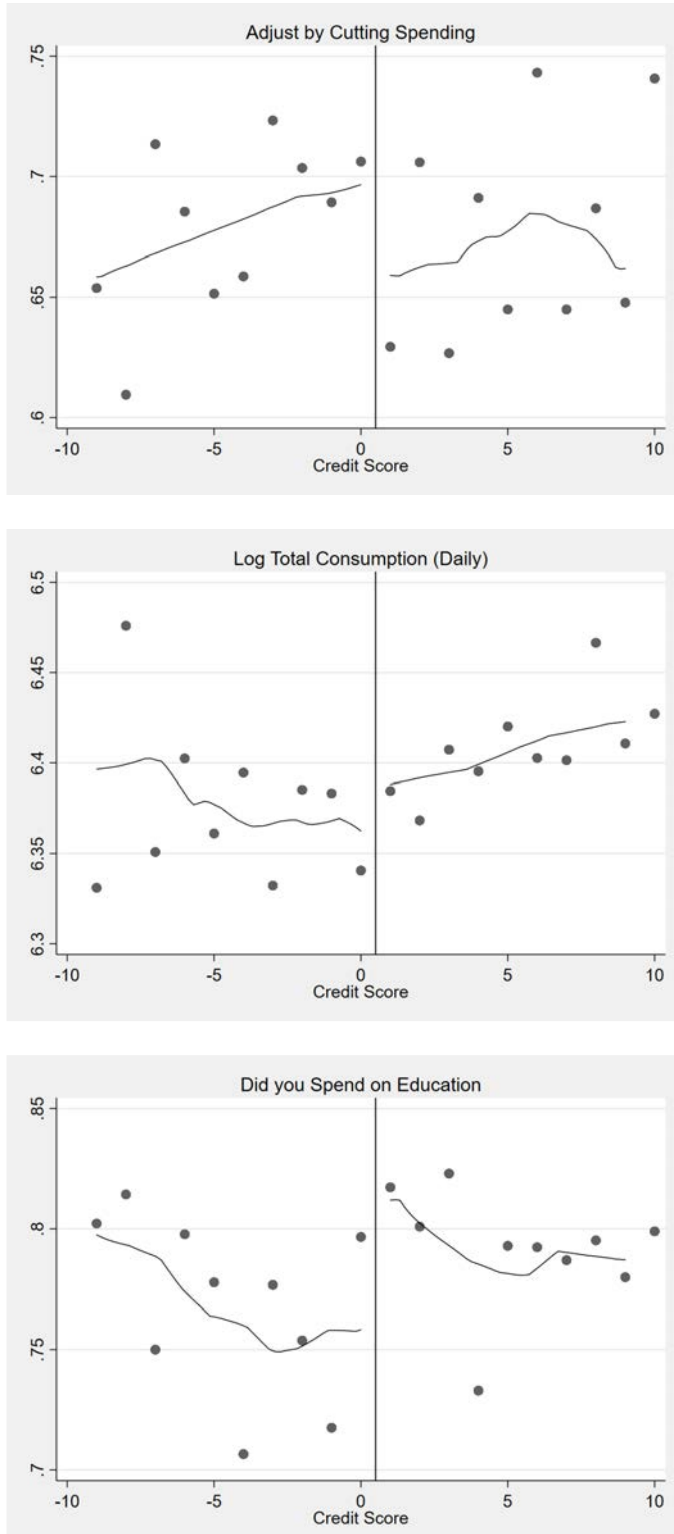
Note: The data covers all M-Shwari loans received in the 18 months prior to the sampling for the survey.

Figure 2B: First Stage, Survey Data



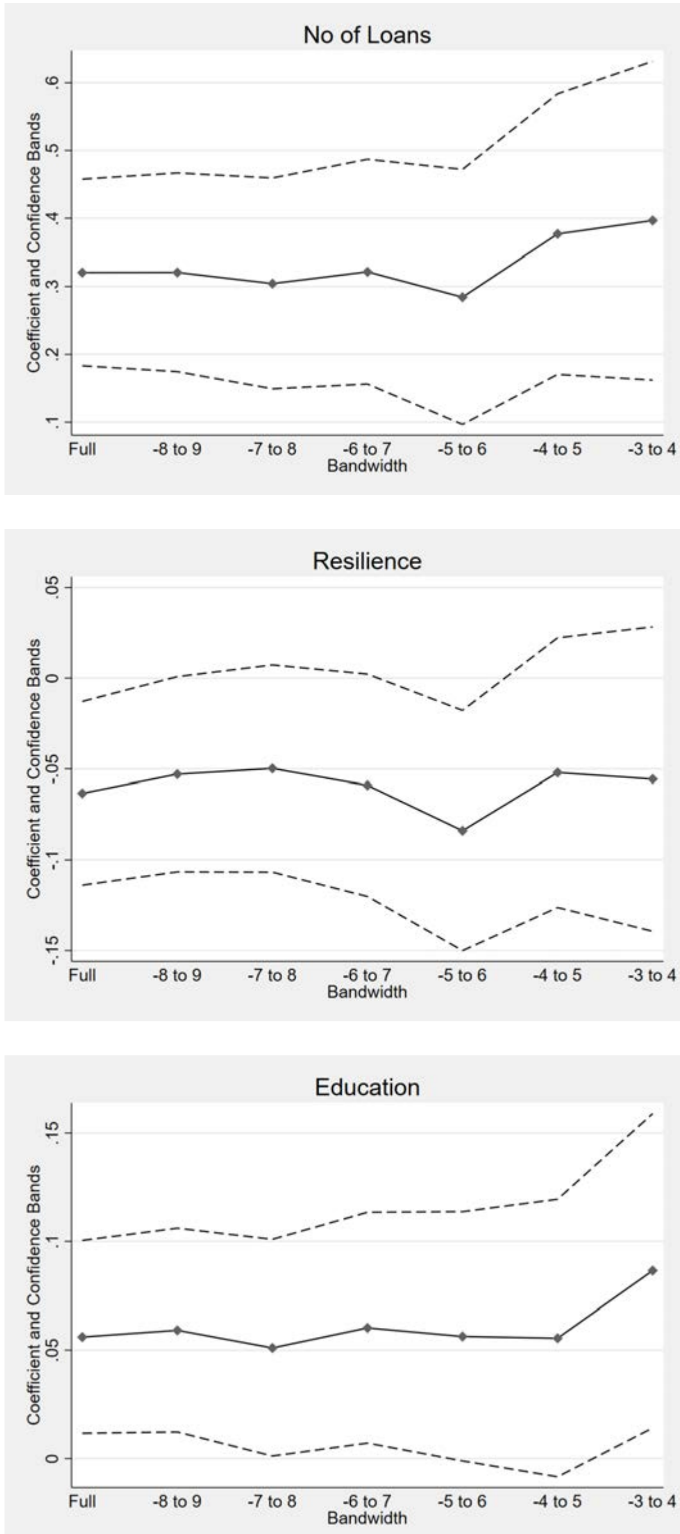
Note: The data covers all loans received in the 2 years prior to the survey from all sources, not just M-Shwari.

Figure 3: Resilience and Expenditures



Note: The first panel shows survey data on whether the household cut epenses of any sort to deal with a negative shock.
The second panel shows survey data on total daily household consumption (in logs).
The third panel shows survey data on whether the household spent on education in the past year).

Figure 4: Robustness to Bandwidth



Note: All three panels shows robustness of the estimated RD coefficient (from equation (1)) to varying bandwidths.
The outcome in the first panel is the number of loans borrowed in the 2 years priot to the survey.
The outcome in the second panel is whether the household cut epenses of any sort to deal with a negative shock.
The outcome in the third panel is whether the household spent on education in the past year).

Table 1A: Summary Statistics from Administrative Data

	Mean	SD	N
Age of Customer	30.462	14.106	6000
Male, M-Shwari Admin Data	.483	.5	6000
Top Up Amount	4670.494	4478.503	5000
Number of Loans	16.823	41.351	5000
Number of Low Days	103.614	54.279	5000
Total MPESA Transaction Value	4047.174	11607.49	5000
Six month Balance	569.078	6725.829	5000
One month Balance	607.158	6638.072	5000
Send Clients	3.299	5.024	5000
Paybill	2.995	13.266	5000
Paybill Clients	.446	.986	5000
Bank Clients	.183	.483	5000

Note: All variables are for the six months prior to the individual opening an M-Shwari account.
Top up is the amount of airtime purchased.
Number of loans is the number of times the individual has taken out an airtime loan.
Low days is the number of days the customer has had less than 2 shillings (USD 0.02) of airtime balance.
Total Value is the value of total inflows (money received plus deposits made plus any bank transfers).
1month/6month Balance is the average daily balance in the persons account in the past 1 month/6 months.
Send clients is the number of unique individuals money is sent to via MPESA by the customer.
Paybill is the number of paybill payments made over M-PESA.
Paybill clients is the number of unique organizations the individual has paid on M-PESA using the paybill service.
Bank clients is the number of unique bank accounts that the customer transferred money from.

Table 1B: Summary Statistics, Survey Data

	Mean	SD	N
Household Size	4.395	2.366	4136
No of Girls in the Household	1.02	1.158	4136
No of Boys in the Household	.916	1.085	4136
Number of Adults	2.46	1.262	4136
Household Head Age	36.646	12.672	3949
Religion is Catholic	.267	.443	4136
HH Head Years of Education	10.775	3.723	3956
Spouse Years of Education	10.044	3.551	2711
Acres of Urban Land Owned	.117	.558	4025
Acres of Rural Land Owned	1.658	2.488	3815
Moved in Last 6 Months	.133	.34	4136
Household Taken a Loan (Dummy)	.506	.5	4136
No of Outstanding Loans	.884	1.42	4109
Total Debt	16070.26	62902	4136
Total Amount of Formal Loans	15631.32	62331.02	4136
Have an M-Shwari Loan	.275	.446	4136
Have a Bank Loan	.059	.235	4136
Have an MFI loan	.019	.136	4136
Have a SACCO Loan	.045	.207	4136
Have a ROSCA Loan	.056	.23	4136
Loan for Emergency	.115	.319	4136
Loan for a Large Purchase	.061	.239	4136
Loan for Everyday Use	.169	.374	4136
Loan To Pay Off Other Debt	.026	.158	4136
Loan For School Fees	.11	.312	4136
Loan For Medical Expenses	.031	.173	4136
Loan for Business	.071	.256	4136
Number of Savings Instruments	3.734	1.74	4136
Saved Last Month	.821	.384	4136
Total Savings in Last Month	7511.921	9861.934	3930
Current Savings Balance Positive	.645	.479	4136
Total Current Balance	7743.302	13295.56	3930
Log Total Assets	10.976	1.503	4048
Log Productive Assets	9.757	1.649	3962
Log Total Consumption (Daily)	6.388	.741	4121
Log Food Consumption (Daily)	5.07	.702	4041
Log Expenditure on Basics	4.261	1.195	3780
Spent on Education?	.769	.422	4121
Spent on Medical Care?	.529	.499	4121
Spent on Clothing?	.716	.451	4121
Spent on Assets?	.818	.386	4121
Spent on Transport?	.731	.443	4121
Spent on Temptation Goods?	.771	.42	4121
Spent on Alcohol, Tobacco?	.082	.275	4121
Negative Shock	.897	.304	4136
Positive Shock	.162	.368	4136
Adjust by Cutting Spending	.63	.483	4136
Shock Response Foregone a Meal	.411	.492	4136
Shock Response Foregone Medical	.263	.44	4136
Shock Response Reduce Non Food	.446	.497	4136
Shock Response Child Out of Sch	.409	.492	4136
Left a Job in Response to Shock	.259	.438	4136
Sold Assets in Response to Shock	.221	.415	4136

Table 1C: Summary Statistics, by Treatment (Above Cutoff) and Control (Below Cutoff)

	Mean, T	SD, T	Mean, C	SD, C
No of Outstanding Loans	1.003	1.506	.766	1.32
Total Debt	17537.52	67057.63	14622.74	58493.96
Total Amount of Formal Loans	16955.13	66293.29	14325.31	58144.65
Have an M-Shwari Loan	.34	.474	.21	.407
Have a Bank Loan	.06	.237	.057	.232
Have an MFI loan	.019	.135	.019	.137
Have a SACCO Loan	.047	.212	.043	.202
Have a ROSCA Loan	.058	.235	.054	.226
Loan for Emergency	.137	.344	.093	.291
Loan for a Large Purchase	.065	.247	.057	.231
Loan for Everyday Use	.195	.396	.143	.35
Loan To Pay Off Other Debt	.029	.168	.022	.147
Loan For School Fees	.119	.324	.1	.3
Loan For Medical Expenses	.036	.185	.026	.16
Loan for Business	.073	.26	.068	.252
Number of Savings Instruments	3.78	1.773	3.689	1.707
Saved Last Month	.813	.39	.829	.377
Total Savings in Last Month	7511.004	9942.155	7512.827	9784.478
Current Savings Balance Positive	.637	.481	.652	.476
Total Current Balance	7617.55	13335.59	7868.415	13257.81
Log Total Assets	10.948	1.529	11.004	1.478
Log Productive Assets	9.738	1.666	9.775	1.633
Log Total Consumption (Daily)	6.401	.751	6.376	.731
Log Food Consumption (Daily)	5.082	.691	5.058	.713
Log Expenditure on Basics	4.281	1.172	4.242	1.216
Spent on Education?	.779	.415	.759	.428
Spent on Medical Care?	.531	.499	.527	.499
Spent on Clothing?	.703	.457	.729	.445
Spent on Assets?	.815	.388	.821	.384
Spent on Transport?	.73	.444	.732	.443
Spent on Temptation Goods?	.778	.416	.765	.424
Spent on Alcohol, Tobacco?	.083	.276	.081	.274
Negative Shock	.902	.297	.892	.31
Positive Shock	.155	.362	.169	.374
Adjust by Cutting Spending	.633	.482	.628	.484
Shock Response Foregone a Meal	.409	.492	.412	.492
Shock Response Foregone Medical	.251	.434	.274	.446
Shock Response Reduce Non Food	.456	.498	.437	.496
Shock Response Child Out of Sch	.416	.493	.402	.49
Left a Job in Response to Shock	.267	.443	.25	.433
Sold Assets in Response to Shock	.219	.414	.223	.416

Note: T stands for individuals in the treatment group (i.e. those with a credit score above the cutoff for a loan.
C stands for individuals in the control group (i.e. those with a credit score below the cutoff for a loan.

Table 1D: Summary Statistics (Separate Sample)

	Mean	SD	N
Loans	7.412	6.158	9993
Loans per Month	.567	.468	9993
Loan Amount	8265.54	16313.89	9993
Months Account Open	13.115	1.188	9993
Loans (RD Sample)	6.559	5.833	1472
Loans per Month (RD Sample)	.511	.453	1472
Loan Amount (RD Sample)	3217.19	5870.489	1472
Months Account Open (RD Sample)	12.932	1.198	1472

Note: This is from a different sample of M-Shwari customers than the study sample (see text for details). The first rows report results for the full sample across the full distribution of credit scores.

Table 2A: Balance in Admin Data

	Characteristics		Airtime			M-PESA Transactions						
	(1) Age	(2) Male	(3) Top Up	(4) No of Loans	(5) Low Days	(6) Value	(7) 6m Bal	(8) 1m Bal	(9) Send	(10) Pay Bill	(11) Pay Bill Clients	(12) Bank Clients
Score Cutoff	-0.869	-0.041	94.128	-0.439	2.472	57.643	110.795	127.912	-0.428	-0.592	-0.057	-0.046
	[0.724]	[0.026]	[272.907]	[2.249]	[3.037]	[725.367]	[551.361]	[532.054]	[0.280]	[0.760]	[0.055]	[0.028]
Control Mean	30.415	0.491	4502.967	16.653	104.642	4017.090	497.585	533.502	3.143	2.597	0.432	0.184
Observations	6000	6000	5000	5000	5000	5000	5000	5000	5000	5000	5000	5000

Note: Robust standard errors in brackets.
All the variables in columns (3) through (12) are for the six months prior to the individual opening an M-Shwari account.
Top up is the amount of airtime purchased.
Number of loans is the number of times the individual has taken out an airtime loan.
Low days is the number of days the customer has had less than 2 Kenyan shillings (USD 0.02) of airtime balance on their account.
Value is the value of total inflows (money received plus deposits made plus any bank transfers).
1m/6m Bal is the average daily balance in the persons account in the past 1 month/6 months.
Send is the number of unique individuals money is sent to via MPESA by the customer.
Paybill is the number of paybill payments made over M-PESA.
Paybill clients is the number of unique organizations the individual has paid on M-PESA using the paybill service.
Bank clients is the number of unique bank accounts that the customer transferred money from.
The specification in all columns is as per equation (1) in the paper with differential linear slopes on either side of the cutoff.
The bandwidth in all columns is -9 to 10.

Table 2B: Balance in Survey Data

	Non-Response	Demographics				Characteristics					
	(1)	(2) Size	(3) Girls	(4) Boys	(5) Adults	(6) Age	(7) Catholic	(8) Head Educ	(9) Spouse Educ	(10) Land Owned	(11) Moved
Score Cutoff	-0.003	0.129	0.106	-0.013	0.035	0.870	-0.041	-0.104	0.064	-0.064	0.008
	[0.024]	[0.142]	[0.070]	[0.066]	[0.075]	[0.796]	[0.027]	[0.235]	[0.264]	[0.164]	[0.021]
Control Mean	0.317	4.335	0.991	0.909	2.435	36.429	0.268	10.783	10.053	1.694	0.134
Observations	6000	4136	4136	4136	4136	3949	4136	3956	2711	4136	4136

Note: Robust standard errors in brackets.
Size refers to household size.
Girls, Boys and Adults refer to the numbers of each in the household.
Age refers to the age of the respondent.
Catholic refers to whether the respondent is a Catholic.
Head Educ and Spouse Educ refer to the years of education of the household head and spouse, respectively.
Land Owned refers to the total acres of land owned by the household.
Moved refers to whether anyone is the household has moved in the last 6 months.
The specification in all columns is as per equation (1) in the paper with differential linear slopes on either side of the cutoff.
The bandwidth in all columns is -9 to 10.

Table 3A: First Stage, Access to M-Shwari, Administrative Data

	Has Loan	No of Loans	Total Loan Amount		Average Loan Size		First Loan Default
	(1)	(2)	(3) Level	(4) Log	(5) Level	(6) Log	(7)
Bandwidth of -9 to 10							
RD Cutoff	0.243***	1.307***	1002.957**	1.718***	112.173***	1.374***	0.007
	[0.027]	[0.282]	[445.862]	[0.208]	[28.306]	[0.164]	[0.024]
Control Mean	0.299	1.924	1512.596	2.206	166.307	1.774	0.066
Observations	5000	5000	5000	5000	5000	5000	2380
Bandwidth of -4 to 5							
RD Cutoff	0.192***	0.805*	575.272	1.267***	73.565*	1.029***	0.024
	[0.043]	[0.454]	[610.277]	[0.325]	[40.846]	[0.258]	[0.036]
Control Mean	0.308	1.962	1549.290	2.255	169.070	1.825	0.065
Observations	2571	2571	2571	2571	2571	2571	1246

Note: Robust standard errors in brackets.
All amounts are reported in Kenyan shillings, where the exchange rate is 100 KSh to the USD.
The specification in all columns is as per equation (1) in the paper with differential linear slopes on either side of the cutoff.
The sample in the last column conditions on having at least one loan (else default is not defined).

Table 3B: First Stage, Access to Credit

	(1) Had Any Loan	(2) No of Loans	(3) Total Debt	(4) Log(Total Debt+1)	(5) Formal Debt	(6) Interest Paid	(7) Gave Loan
Bandwidth of -9 to 10							
Score Cutoff	0.106***	0.320***	1758.431	0.882***	1415.405	0.216	0.040
	[0.031]	[0.082]	[3684.916]	[0.275]	[3669.798]	[0.155]	[0.028]
Sidak-Holm p-value	0.006	0.001	0.982	0.013	0.982	0.725	0.725
Control Mean	0.455	0.766	14622.736	3.718	14325.305	0.591	0.293
Observations	4136	4109	4136	4136	4136	4080	4136
Bandwidth of -4 to 5							
Score Cutoff	0.119***	0.377***	5705.199	1.024**	5266.330	0.251	0.051
	[0.045]	[0.124]	[5349.003]	[0.404]	[5326.126]	[0.216]	[0.041]
Sidak-Holm p-value	0.083	0.028	0.838	0.107	0.838	0.838	0.838
Control Mean	0.455	0.764	14283.339	3.688	13943.502	0.488	0.285
Observations	2111	2096	2111	2111	2111	2082	2111

Note: Robust standard errors in brackets.
Interest is reported as a fraction of the daily total expenditure of the household.
The Sidak-Holm p-value accounts for multiple testing across all outcomes in Tables 3B and 3C.
All amounts are reported in Kenyan shillings, where the exchange rate is 100 KSh to the USD.
The specification in all columns is as per equation (1) in the paper with differential linear slopes on either side of the cutoff.

Table 3C: First Stage, Sources of Credit

	(1) MShwari Loan	(2) Bank Loan	(3) MFI Loan	(4) SACCO Loan	(5) ROSCA Loan	(6) Informal Loan
Bandwidth of -9 to 10						
Score Cutoff	0.133***	0.011	0.005	0.003	0.024*	0.001
	[0.028]	[0.015]	[0.008]	[0.012]	[0.014]	[0.015]
Sidak-Holm p-value	0.000	0.970	0.974	0.982	0.591	0.982
Control Mean	0.210	0.057	0.019	0.043	0.054	0.067
Observations	4136	4136	4136	4136	4136	4136
Bandwidth of -4 to 5						
Score Cutoff	0.126***	0.026	0.014	0.018	0.032	-0.019
	[0.041]	[0.022]	[0.011]	[0.019]	[0.022]	[0.022]
Sidak-Holm p-value	0.027	0.838	0.838	0.838	0.757	0.838
Control Mean	0.214	0.054	0.017	0.041	0.053	0.064
Observations	2111	2111	2111	2111	2111	2111

Note: Robust standard errors in brackets.
The Sidak-Holm p-value accounts for multiple testing across all outcomes in Tables 3B and 3C.
The specification in all columns is as per equation (1) in the paper with differential linear slopes on either side of the cutoff.

Table 4A: Resilience

	Shock	Expenses Foregone				Other Adjustments		
	(1)	(2) Any	(3) Meals	(4) Medical	(5) Non-Food	(6) Child Out of School	(7) Left Job	(8) Sold Assets
Bandwidth of -9 to 10								
Score Cutoff	0.013	-0.063**	-0.045	-0.049*	-0.020	0.006	0.026	0.029
	[0.018]	[0.030]	[0.032]	[0.029]	[0.032]	[0.032]	[0.029]	[0.027]
Sidak-Holm p-value			0.896	0.896	0.998	0.998	0.970	0.995
Control Mean	0.892	0.679	0.447	0.300	0.474	0.434	0.266	0.238
Observations	4136	3711	3711	3711	3711	3711	3711	3711
Bandwidth of -4 to 5								
Score Cutoff	0.006	-0.052	-0.095**	-0.081*	-0.033	0.080*	0.015	0.002
	[0.026]	[0.044]	[0.047]	[0.042]	[0.047]	[0.047]	[0.042]	[0.039]
Sidak-Holm p-value			0.362	0.629	0.919	0.909	0.926	0.919
Control Mean	0.901	0.698	0.462	0.297	0.486	0.434	0.263	0.219
Observations	2111	1913	1913	1913	1913	1913	1913	1913

Note: Robust standard errors in brackets.
Sample restricted to households with a negative shock (90% of the sample).
The specification in all columns is as per equation (1) in the paper with differential linear slopes on either side of the cutoff.

Table 4B: Resilience, Heterogeneoity by Cause of Shock

	(1) Weather	(2) Disease	(3) Fire	(4) Theft	(5) Death	(6) Illness	(7) Injury	(8) Livestock	(9) Business	(10) Employment
Bandwidth of -9 to 10										
Cutoff*Shock	-0.012	-0.088**	-0.161	-0.015	-0.110*	0.007	-0.002	-0.044	0.019	-0.022
	[0.036]	[0.037]	[0.129]	[0.046]	[0.065]	[0.030]	[0.044]	[0.037]	[0.033]	[0.037]
Score Cutoff	-0.060*	-0.045	-0.063**	-0.064**	-0.056*	-0.069**	-0.061**	-0.053*	-0.069**	-0.054*
	[0.031]	[0.031]	[0.030]	[0.031]	[0.031]	[0.035]	[0.031]	[0.031]	[0.032]	[0.031]
Shock	0.072***	0.165***	0.195**	0.091***	0.020	0.156***	0.124***	0.089***	0.018	0.102***
	[0.025]	[0.025]	[0.090]	[0.033]	[0.044]	[0.022]	[0.032]	[0.025]	[0.023]	[0.026]
Control Mean	0.679	0.679	0.679	0.679	0.679	0.679	0.679	0.679	0.679	0.679
Observations	3711	3711	3711	3711	3711	3711	3711	3711	3711	3711
Bandwidth of -4 to 5										
Cutoff*Shock	-0.011	-0.106**	-0.038	-0.101	-0.012	-0.014	-0.019	0.008	0.024	-0.014
	[0.050]	[0.051]	[0.214]	[0.062]	[0.087]	[0.042]	[0.060]	[0.052]	[0.046]	[0.051]
Score Cutoff	-0.051	-0.027	-0.052	-0.044	-0.053	-0.050	-0.047	-0.050	-0.059	-0.044
	[0.046]	[0.046]	[0.045]	[0.045]	[0.045]	[0.051]	[0.045]	[0.046]	[0.047]	[0.046]
Shock	0.080**	0.167***	0.020	0.152***	-0.057	0.179***	0.157***	0.069*	0.001	0.092***
	[0.034]	[0.033]	[0.170]	[0.042]	[0.062]	[0.030]	[0.040]	[0.036]	[0.033]	[0.035]
Control Mean	0.698	0.698	0.698	0.698	0.698	0.698	0.698	0.698	0.698	0.698
Observations	1913	1913	1913	1913	1913	1913	1913	1913	1913	1913

Note: Robust standard errors in brackets.
Sample restricted to households with a negative shock (90% of the sample).
The last three columns are shocks that results in losses of livestock, business and employment, respectively.

Table 5: Consumption

	Log Expenditures				Dummy for Positive Expenses					
	(1) Total	(2) Food	(3) Basics	(4) Airtime	(5) Education	(6) Health	(7) Clothing	(8) Assets	(9) Temptation Goods	(10) Alcohol Tobacco
Bandwidth of -9 to 10										
Score Cutoff	0.017	0.035	0.043	0.063	0.058**	-0.046	-0.021	-0.025	-0.001	0.010
	[0.048]	[0.047]	[0.082]	[0.065]	[0.027]	[0.032]	[0.030]	[0.025]	[0.027]	[0.017]
Sidak-Holm p-value		.	1.000	1.000	0.743	0.970	0.999	0.999	1.000	1.000
Control Mean	6.377	5.054	4.238	3.385	0.771	0.547	0.730	0.834	0.786	0.081
Observations	3701	3637	3405	3479	3701	3701	3701	3701	3701	3701
Bandwidth of -4 to 5										
Score Cutoff	0.009	0.102	-0.015	0.034	0.059	-0.045	-0.021	-0.057	0.005	-0.001
	[0.072]	[0.068]	[0.119]	[0.096]	[0.038]	[0.047]	[0.044]	[0.037]	[0.039]	[0.025]
Sidak-Holm p-value		.	0.999	0.999	0.765	0.988	0.999	0.988	0.999	0.999
Control Mean	6.366	5.052	4.194	3.354	0.752	0.564	0.721	0.838	0.775	0.063
Observations	1907	1871	1765	1792	1907	1907	1907	1907	1907	1907

Note: Robust standard errors in brackets.
For expenditures, basics covers all utilities (water, rent, electricity, firewood, fuel and gas).
For expenditures, temptation goods include meals outside the house, alcohol, tobacco, entertainment, donations and events.
The specification in all columns is as per equation (1) in the paper with differential linear slopes on either side of the cutoff.

Table 6: Assets (Financial and Real)

	Savings Instruments	Savings Last Month		Savings Current Balance		Log Asset Value	
	(1) Number Used	(2) Any	(3) Amount	(4) Any	(5) Amount	(6) Total	(7) Productive
Bandwidth of -9 to 10							
Score Cutoff	0.184*	0.007	-5.716	0.011	243.889	0.022	0.055
	[0.107]	[0.023]	[631.385]	[0.029]	[833.840]	[0.095]	[0.105]
Sidak-Holm p-value	0.940	1.000	1.000	1.000	1.000	1.000	1.000
Control Mean	3.689	0.829	7512.827	0.652	7868.415	11.004	9.775
Observations	4136	4136	3930	4136	3930	4048	3962
Bandwidth of -4 to 5							
Score Cutoff	0.272*	0.018	437.442	0.053	1919.968	0.254*	0.275*
	[0.157]	[0.034]	[935.513]	[0.043]	[1214.336]	[0.139]	[0.153]
Sidak-Holm p-value	0.940	1.000	1.000	1.000	1.000	1.000	1.000
Control Mean	3.676	0.831	7718.806	0.648	7879.983	10.941	9.740
Observations	2111	2111	2002	2111	2012	2069	2025

Note: Robust standard errors in brackets.
For assets, productive assets include mobile phones, livestock, computers and vehicles.
All amounts are reported in Kenyan shillings, where the exchange rate is 100 KSh to the USD.
The specification in all columns is as per equation (1) in the paper with differential linear slopes on either side of the cutoff.