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Fintech and household resilience to shocks: Evidence from digital loans in Kenya[☆]

Tavneet Suri [a,*], Prashant Bharadwaj [b], William Jack [c]

[a] MIT Sloan School of Management, United States of America
[b] Department of Economics, UC San Diego, United States of America
[c] Department of Economics, Georgetown University, United States of America

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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. Fintech tools can be a crucial way to improve financial access and household resilience.

1. Introduction

There is little doubt that advances at the intersection of finance and technology (fintech) have already started transforming markets in the developing world. Innovations like mobile payment systems and P2P lending platforms are revolutionizing the way people pay, consume, and transact with one another (Suri, 2017). One of the key areas in the developing world where fintech innovations can be particularly transformative is in helping smooth consumption in response to shocks (Jack and Suri, 2014). Perhaps much more so than their developed country counterparts, the poor in developing countries have income sources that are subject to shocks, the consequences of which are made severe due to lack of social safety nets and negligible financial substitutes. As a result, 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. – can be a barrier. In this paper, we 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 (see Goldsteing et al., 2019 for a recent overview), 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 providing 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 them, without crowding out 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

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* Correspondence to: E62-524, 100 Main Street, Cambridge MA 02142, United States of America.
E-mail address: tavneet@mit.edu (T. Suri).

[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.

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launched in 2012 through a partnership between the 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 (140% annual rate, also known as a "loan facilitation fee")[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 KSh 4000 (approximately 40 USD).[3]

Part of the sustainability of the digital credit model relies on being able to access many more customers than would be possible under conventional methods of credit delivery. Since such loans can allow banks to lower their administrative costs tremendously, it is likely (but not precisely documented until this study) that these loans have high demand. We also do not know how these loans affect individuals' economic wellbeing. In this paper, we aim to fill this gap: in particular, we present results on the impacts of this digital loan product in Kenya on credit take up and resilience to household shocks. In recent years, Kenya's mobile money revolution has transformed how people transact and smooth shocks (Jack and Suri, 2014). While mobile money has revolutionized how people transfer and save money or pay for purchases, the impacts of digital loans has yet to be studied. Understanding the impacts of having access to such loans is crucial for fine-tuning developing country policies in the area of financial access. As short term loans become common in the developing world, understanding demand for these products and their impacts will be key.

To estimate the take up and impacts of these loans we use a fuzzy 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 they are eligible for a loan and how much they have 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 became eligible 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. The take up rate is different across the credit score cutoff even 18 months after the accounts were opened even though some people below the cutoff initially do get loans later as they improve their standing with the bank. However, the take up difference remains. In addition, there is a large difference across the cutoff in the total amount borrowed at the end of 18 months.

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 over a time span of almost two years. 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). They are also 24 percentage points more likely to have an M-Shwari loan than the control. Looking at the total amount borrowed (across all loans), those eligible have borrowed 90% more than the control at the end of two years. 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 other formal or informal sources). 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 loans amounts from M-Shwari that are 180% more than the control.[6] Given the high interest rates associated with M-Shwari and other digital lenders (some are as high as 215% per annum) there has been some concern in policy circles and the press about indebtedness. We address this directly in our analysis and show the M-Shwari loans do not cause a significant change in the debt burden for customers.

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. While this is a high number, we emphasize that our sample is precisely made up of fairly poor and vulnerable individuals as the RD bandwidth focuses around the point where individuals are just eligible and ineligible for this digital loan product. 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 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 probability that households spend on education and on the levels of spending on

[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.

[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. Survey can be accessed from the corresponding author's website.

education when winsorized (the consumption estimates are noisy for all consumption categories, but economically meaningful in size for 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 statistically insignificant impacts on a host of other wealth related outcomes such as savings and asset ownership (though some of these effects are economically meaningful in size but are unfortunately measured with noise); 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 focused on the issue of relatively low take up in the context of microfinance (see Banerjee et al., 2015a,b). 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. In addition, we find that M-Shwari does not substitute for other forms of finance, but truly expands credit access (in contrast to Tang, 2019 who shows that fintech driven peer to peer lending can substitute for formal sources of credit in the US). 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 contribute to a burgeoning literature on mobile money and digital banking in the developing world. Focussing on digital banking,[8] an excellent example of such work is Bastian et al. (2018) who study a related product to M-Shwari called M-Pawa in Tanzania. In their experiment, they find that providing access to digital banking to female entrepreneurs leads them to save more in the digital platform relative to other forms of savings, and also increases reported control over finances intended for their businesses. Our results on improved resilience speak to the recent work by Lee et al. (2021) who randomize mobile banking to poor households and migrants in Bangladesh. Digital banking significantly improves how migrants are able to send back remittances and this crucially improves consumption during the lean season.

Our results on resilience also contribute towards an understanding of the role of small, short term credit (even if delivered through non-digital mechanisms) in developed and developing countries.[9] In the developed country setting, a closely related area given the immediacy and size of the loans we study is the research in consumer finance on payday loans in the US. Important work in this area finds that while access to credit allows individuals to smooth during certain shocks (Morse, 2011; Zinman, 2010), the high interest rates charged by these loans often end up harming borrowers (Skiba and Tobacman, 2011; Melzer, 2011). Perhaps as a way to resolve this concern, many researchers have focused 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.

The work in developing countries when it comes to short term credit has traditionally focussed on microfinance. While microcredit and its impact on capital related investments has been the focus in this space, several papers examine the role of microcredit in helping households cope with shocks (Islam and Maitra, 2012; Mitra et al., 2015). As further examples, Karlan and Zinman (2011) find that net borrowing increases when microfinance clients were offered individual (as opposed to group) liability loans, but both business activity and subjective well-being fall as a result, although the loans help borrowers cope with risk. Tarozzi et al. (2015) report similarly mixed evidence of access to microcredit in Ethiopia. Our work is directly related to these but also to an older and broader literature showing the use of various financial products (not just credit related products) in mitigating risk, improving resilience, and helping smooth consumption in developing countries (Deaton, 1989; Alderman and Paxson, 1994; Besley, 1995; Dercon, 2002).

2. 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 an application on an account holder's phone (not necessarily a smartphone). Loans are disbursed 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 commitment savings account) and the opportunity to get short term loans. At a broad level there is no real competitor for digital loans. These loans were designed to reach those without credit files in the credit bureau, people who had little to no access to loans from the formal sector and without any collateral, group liability or even social collateral (such as peer pressure) requirements.

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 Fig. 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 tremendously and, as can be seen from this Fig. 1A, it all comes from an expansion in the number of small value deposit accounts, i.e. M-Shwari.

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 (USD 100), 3% for balances up to KSh 20,000 (USD 200), 4% for balances up to KShs 50,000 (USD 500) 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. The bottom panel in Fig. 1A also shows M-Shwari's market share in digital lending in Kenya in 2017. As can be seen, M-Shwari is the market leader in digital lending. The main competitor is KCB M-PESA which is almost identical to M-Shwari (they

[8] For a review on the impact of mobile money, see Suri (2017). For some examples of research showing the role of mobile money in reducing exposure to risk, see Jack and Suri (2014) and Riley (2018).

[9] While we find effects on resilience, the lack of effects on investments and savings should not be surprising given the size and repayment structure of these loans.

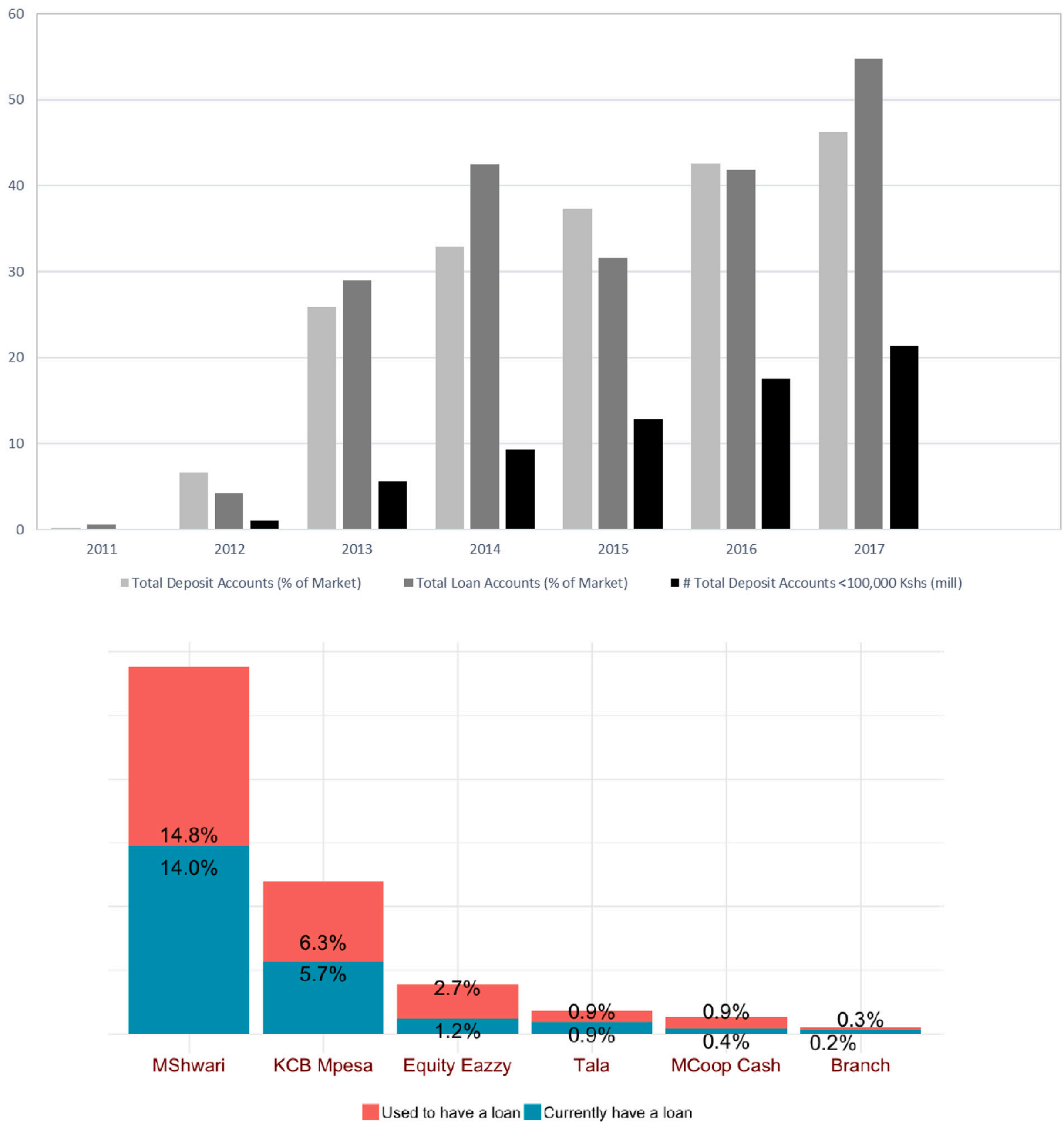

Fig. 1A. CBA Market Share. Note: The top panel shows CBA's overall market share between 2011 and 2017 in Kenya. The data for the top panel comes from the Central Bank of Kenya. The lower panel shows a measure of the market share for M-Shwari's lending product. The data comes from a 2017 survey that asks adults whether they have used or currently borrow on M-Shwari.

offer three different loan lengths but almost all their disbursed loans are identical to the M-Shwari lending product and at similar interest rates) and it uses exactly the same data extracts from the cell phone company to score customers as M-Shwari. The other competing products had little to no market share in Kenya in 2017.

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 USD) but sometimes as high as KSh 10,000 (USD 100). 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 (an annual compounded interest rate of about 140%). 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 user 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 whether or 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). We know the variables that input into the credit score (we discuss these in more detail below) but we do not know exactly how the score is computed, i.e. we do not know the weights the bank uses for each of these variables to create a score. The formula for the credit limits is separate from that determining the original credit scores. Again, we do not know this formula but we know that it uses data on the original score and the savings and borrowing (and repayment) behavior of the customer to decide on changes in limits. 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.

Digital loan products often have high default rates, especially on the first loan that consumers take out (see Carlson (2017)). In our data from M-Shwari, about 9% of customers default on their first loan, which is a lot lower than other digital lending products (Carlson (2017) finds much higher default rates on first loans from a smartphone digital lending product in Kenya). Other formal loan products have much lower default rates as other formal loans tend to be heavily collateralized. However, for the customers in our sample, they do not have many other formal loan alternatives as we describe below.

3. Data

For this study, we use three different datasets. We describe each of these datasets in detail separately.

3.1. Administrative data

The first dataset we use is 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.

To design the study, we used this administrative data 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 (the entire credit score ranges from −150 to +300 as shown in Fig. 1B). 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 the 18 months since they opened their accounts. They are all considered active clients of the bank given when we pulled the data. We do not know the full evolution of their loans or credit histories. A random sample of 6000 of these 156,000 individuals make up the survey sample (as we describe in more detail below).

Fig. 1B shows where in the overall distribution of credit scores our sample is drawn from using this administrative data, i.e. it shows what fraction and where in the distribution of credit scores the −9 to 10 range lies. As can be seen, 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).

Table 1A shows the summary statistics for this administrative data for our overall sample. 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 spends about 4700 KSh (USD 47) in “top up” amounts, which is the amount of prepaid airtime purchased. They take out 17 loans of a prepaid airtime, a product called *Okoa Jahazi*,[10] they experience 103 “low days”, which is the number of days the customer has had less than KSh 2 (USD 0.02) of airtime balance. Individuals in our sample on average have M-PESA transactions of total value of about KSh 4000 (USD 40), with a six month and one month M-PESA balance of about KSh 600 (USD 6). “Send clients” is the number of unique individuals money is sent to via MPESA (on average 3), “Paybill” is the number of paybill payments made over M-PESA (on average 3), “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 (on average 0.2).

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	11 607.49	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 person’s 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.

3.2. Survey data

To operationalize a study sample, we asked the bank to draw a random sample of 6000 clients who opened up an M-Shwari account between January and March, 2015 and whose credit scores lay between −9 and 10. For 5000 of these 6000 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.[11]

[10] This loan product gives customers between KSh 10 (10 cents) and KSh 1000 (USD 10) of airtime on credit and customers are a charged a 10% fee for the credit which is deducted at disbursal of the credit (i.e. if you request 10 cents you receive 9 cents but have to pay back 10 cents). The credit is paid off through prepaid airtime being deducted at the next time of top up and is required to be paid back in 96 h (if it is not, then the customer cannot access Okoa Jahazi for 7 days).

[11] We only have administrative data on 5000 clients as the bank first sampled 5000 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 1000 clients, but they did not provide us with administrative data aside from the credit score and phone numbers for these 1000.

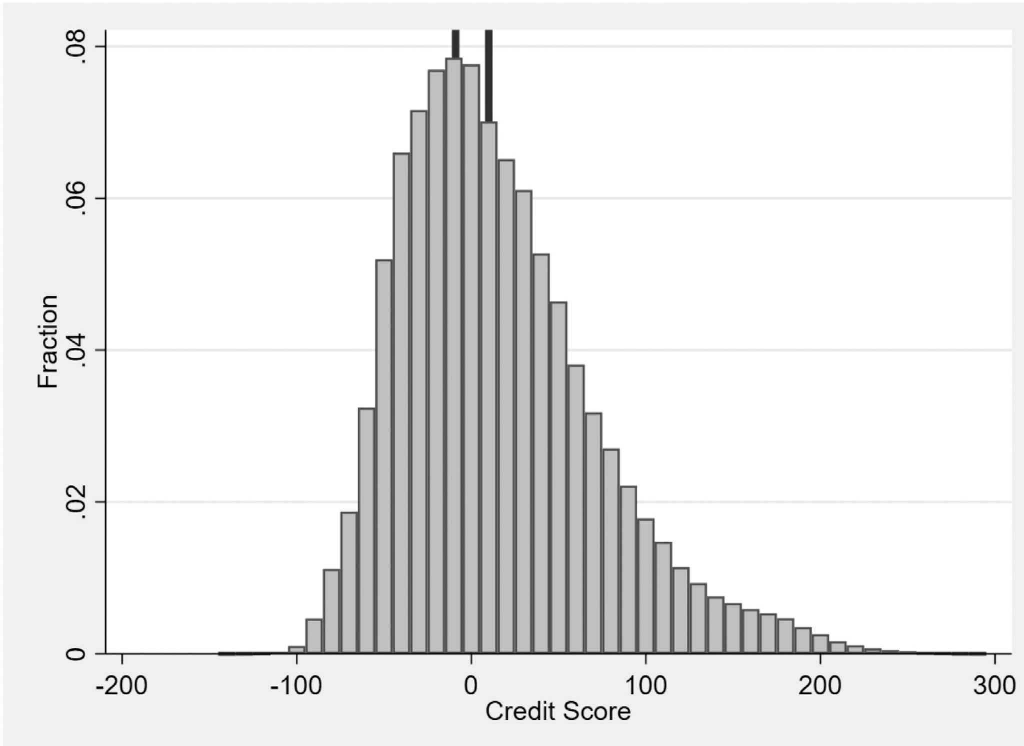

Fig. 1B. Credit Score Distribution. Note: The RD window is marked in black and covers 15% of the overall sample of accounts.

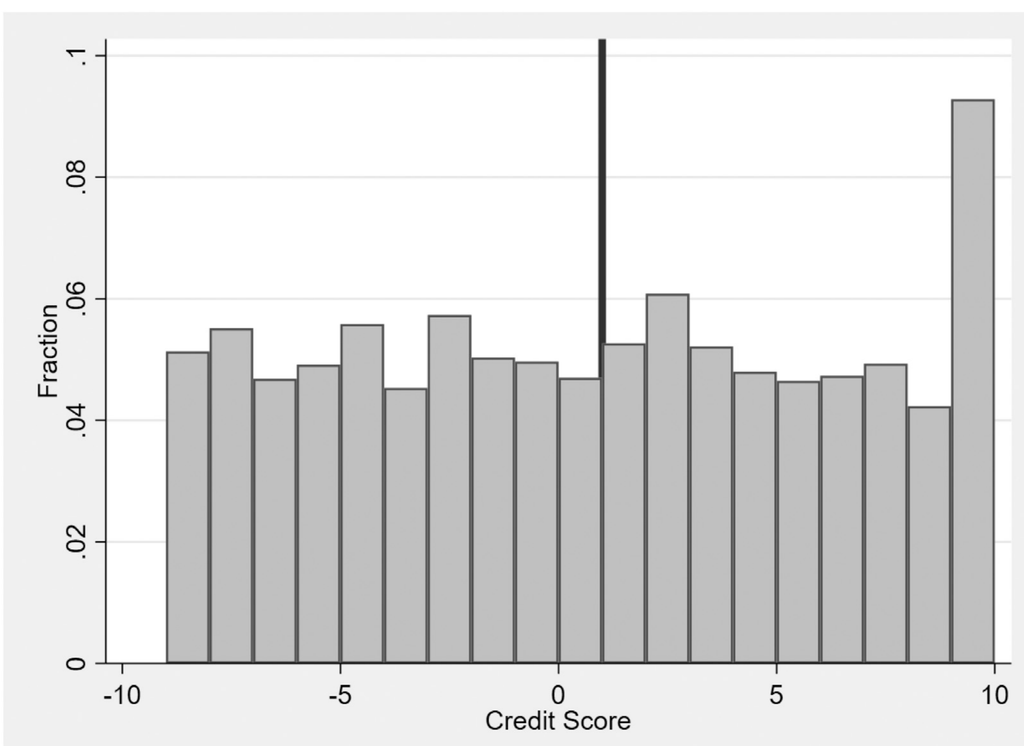

Fig. 1C. Histogram of Credit Score. Note: The survey sample was drawn from M-Shwari customers with credit scores spanning −9 to 10. Individuals were assigned a credit score (that never changes) at the time of account opening. Individuals with a credit score strictly above zero were eligible for loans of varying sizes (depending on the score).

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	16 070.26	62 902	4136
Total amount of formal loans	15 127.68	62 300.89	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	13 295.56	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	17 537.52	67 057.63	14 622.74	58 493.96
Total amount of formal loans	16 531.79	66 194.71	13 742.45	58 187.57
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	13 335.59	7868.415	13 257.81
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).

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. Fig. 1C shows the distribution of credit scores around the credit score cutoff in our survey sample of 6000 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.

We then attempted to survey these 6000 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, almost two years after these individuals opened their M-Shwari accounts.[12] Tables 1B and 1C report some of the basic characteristics of our sample. Table 1B shows the summary statistics from the survey data 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).

Table 1B shows that 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 7743 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.

[12] The survey instrument is posted at https://mitmgmtfaculty.mit.edu/tsuri/. For the survey, we gave individuals prepaid cell phone credit worth $3 to cover their opportunity costs of time and the costs of charging their phones.

Table 1D
Summary statistics, compared to 2016 FinAccess survey.

	Mean, our study 2016	SD, our study 2016	Mean, FinAccess 2016	SD, FinAccess 2016
Household size	4.395	2.366	4.392	2.486
Number of adults	2.46	1.262	2.16	1.169
Head has completed primary	.173	.378	.099	.299
Head has completed secondary	.301	.459	.078	.268
Head has completed university	.057	.232	.022	.145
Spouse has completed primary	.214	.41	.179	.384
Spouse has completed secondary	.283	.45	.112	.316
Spouse has completed university	.027	.163	.089	.285
Negative shock	.897	.304	.798	.402
Adjust by cutting spending	.63	.483	.529	.499
Shock response foregone a meal	.411	.492	.423	.494
Shock response foregone medical	.263	.44	.345	.475
Shock response reduce non food	.446	.497	.074	.262
Shock response child out of Sch	.409	.492	.003	.051

Note: Our study refers to data from our phone survey (the whole sample, 4136 observations) collected between Sept 2016 and Jan 2017. Unit of observation was the household.
The FinAccess 2016 was a survey conducted by Financial Sector Deepening in Kenya, with a sample size of 8665 individuals.
Most of the data in the FinAccess survey is collected at the individual level as opposed to the household level.
Here, we report summary statistics for the set of variables collected at the household level that are comparable to our phone survey.

Table 1E
Summary statistics, compared to 2019 FinAccess survey.

	Mean, our study 2016	Mean, FinAccess 2019	Mean, FinAccess 2019 subsample
Household size	4.395	3.974	3.265
Head has completed primary	.173	.205	.196
Head has completed secondary	.301	.167	.275
Head has some university	.057	.048	.137
Owns any land?	.62	.576	.502
Less than 30 min walk to bank	.815	.551	.77
Less than 60 min walk to bank	.971	.759	.879
More than 180 min walk to bank	.001	.112	.059
Less than 30 min walk to MM	.951	.989	.987
Less than 60 min walk to MM	1	.971	.923
More than 180 min walk to MM	0	.329	.089
Airtime consumption (Daily)	43.53	32.179	61.559
Education consumption (Daily)	84.713	125.14	196.941
Medical consumption (Daily)	27.228	26.571	45.177
Transport consumption (Daily)	40.347	44.15	80.326
Utilities consumption (Daily)	110.985	54.999	114.202
Spent on airtime?	.991	.868	.995
Spent on education?	.769	.674	.689
Spent on medical care?	.529	.576	.699
Spent on transport?	.731	.741	.852
Spent on utilities?	.942	.569	.832

Note: Our study refers to data from our phone survey, with 4,136 observations where the unit of observation was the household.
The FinAccess 2019 was a survey conducted by Financial Sector Deepening in Kenya and the Central Bank of Kenya in 2018, with a sample of 8,669 individuals.
Most of the data in the FinAccess survey is collected at the individual level as opposed to the household level.
Here, we report summary statistics for the set of variables collected at the household level that are comparable to our phone survey.
The las column restricts the FinAccess data to the subsample that had ever taken out a mobile banking loan, a sample of 957 individuals.

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.

As mentioned above, the average loan size on M-Shwari is $4.8 so it is worth discussing some of the consumption summary statistics in a little more detail. Total daily household consumption is about $8 in our sample. This is spent across a wide variety of items. Food and necessities make up about $6 of that and utilities another $1.10, on average. Of course, there are long right tails in a lot of the expenditure variables so the medians are quite different, at $5 and $0.80, respectively. For those households that do spend on medical, the median expense on medical care is $0.25 per day, or $7.50 in the last month.

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.

Tables 1B and 1C also give a sense of the debt held by these households and what the alternatives to M-Shwari may be. For the loan data, we asked the individual to list all the loans they or others in their household had taken out in the past two years. And then for each loan, we asked the date, the amount that was borrowed, the installments, the interest rate, the purpose of the loan and the source of the loan. As can be seen from Tables 1B and 1C, 34% of households had taken loans from M-Shwari, whereas very few had taken loans from other sources, even in the control group. In the control group, only 6% of households had taken a bank loan, only 2% a loan from an MFI, only 4% a loan

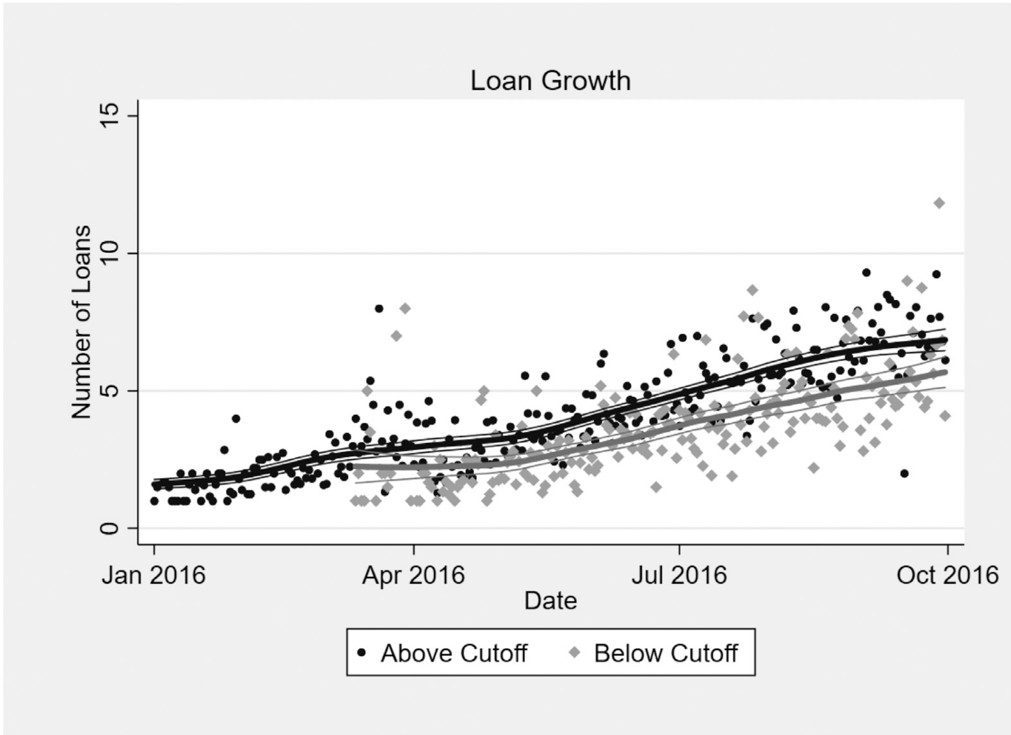

Fig. 1D. Loan History (Separate Sample, RD Bandwidth). Note: The survey sample was drawn from M-Shwari customers with credit scores spanning −9 to 10. This graph is from a different sample of M-Shwari customers than the study sample (see text for details). Individuals in this sampled opened accounts in January 2016 and the data runs till the end of March 2017.

from a SACCO, only 5% a loan from a ROSCA and only 7% a loan from informal sources.[13]

In Table 1D, we show some summary statistics for a random sample of adults in Kenya, collected in 2016 by Financial Sector Deepening called the FinAccess survey.[14] This survey is focused on better understanding financial access and inclusion for a random sample of adults in the country. The survey therefore largely asks questions at the individual level and not at the household level. In Table 1D we only show summary statistics for the subset of variables that are collected at the household level and in the same way across both datasets. As can be seen from this table, our study sample has the same sized households as the national average, though there are slightly fewer adults in the households in our sample. It seems the household heads are more educated in our sample, though this is not necessarily true for spouses of the head. Our sample is more likely to experience a negative shock in the last year but the propensity to cut various expenditures in response are quite similar in terms of food, less so for non-food.

To provide additional information on “who” our sample is, we compare our sample to individuals in FinAccess Survey from 2019 in Table 1E. While this survey is from a time that is after our survey, there are two advantages to this comparison. First, it has more comparable variables to our survey than the 2016 data (from Table 1D); in particular, it collected household level consumption data and access to banks and mobile money agents, which are particularly relevant in our case. The second advantage is that by 2019, many more Kenyans had accounts on mobile banking (defined in the 2019 FinAccess survey as M-Shwari, KCB M-PESA and Equitel Money) than in 2016. So we can restrict the FinAccess sample to those with a loan from mobile banking and compare our sample to those individuals. In Table 1E, we therefore compare our sample to the FinAccess 2019 overall sample (8669 individuals) as well as the sub-sample with a mobile banking loan (957 individuals). As we can see from Table 1E, our sample is richer (higher consumption) than the average in the 2019 FinAccess but very similar to those that have mobile banking loans. Our sample also has similar access to banks and mobile money agents as those that borrow from a mobile banking platform in 2019 in the FinAccess data.

Table 1F
Summary statistics (Separate Sample).

	Mean	SD	N
Loans	7.412	6.158	9993
Loans per month	.567	.468	9993
Loan Amount	8265.54	16 313.89	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 row reports results for the full sample across the full distribution of credit scores.

Finally, it is worth discussing response rates to the phone survey. While survey response rates are rather high (from a sample of 6000, we were able to reach 4136 households, i.e. a 69% completion rate), it is also important that we find that the non-response is not differential across the credit score 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.

3.3. Separate sample administrative data

Finally, in order to show some more descriptives on the evolution of loan amounts and limits, we obtained data from the bank on a

[13] Informal sources combines loans from a church or religious group, an employee, an employer, a informal moneylender, a friend or a family member.
[14] This data is available online at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/QUTLO2.

Table 2A
Balance in admin data.

	Characteristics		Airtime			M-PESA transactions						
	(1) Age	(2) Male	(3) Top Up	(4) Loans	(5) Low days	(6) Value	(7) 6m bal	(8) 1m bal	(9) Send	(10) Pay bill	(11) PB clients	(12) Bank clients
Bandwidth of −9 to 10												
Score cutoff	−0.869	−0.041	0.031	−0.439	2.472	−0.089	−0.335**	−0.351**	−0.428	−0.592	−0.057	−0.046
	[0.724]	[0.026]	[0.049]	[2.249]	[3.037]	[0.084]	[0.156]	[0.160]	[0.280]	[0.760]	[0.055]	[0.028]
Control mean	30.415	0.491	8.758	16.653	104.642	7.755	3.421	2.540	3.143	2.597	0.432	0.184
Observations	6000	6000	5000	5000	5000	5000	5000	5000	5000	5000	5000	5000
Bandwidth of −4 to 5												
Score cutoff	−0.589	−0.071*	0.061	−0.998	−7.562*	−0.035	−0.249	−0.413*	−0.528	0.132	−0.031	0.015
	[1.056]	[0.037]	[0.069]	[3.253]	[4.425]	[0.126]	[0.227]	[0.231]	[0.409]	[1.124]	[0.078]	[0.042]
Control mean	30.941	0.495	8.793	16.463	102.759	7.833	3.559	2.634	3.308	2.931	0.435	0.209
Observations	3059	3059	2571	2571	2571	2571	2571	2571	2571	2571	2571	2571

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 in column (3) is the amount of airtime purchased.
Loans in column (4) is the number of times the individual has taken out an airtime loan.
Low days in column (5) is the number of days the customer has had less than 2 Kenyan shillings (USD 0.02) of airtime balance on their account.
Value in column (6) is the value of total inflows (money received plus deposits made plus any bank transfers). Measured as the arsinh (inverse hyperbolic sine) of the value.
1m/6m Bal in columns (7) and (8) is the average daily balance in the person's account in the past 1 month/6 months. Measured as the arsinh (inverse hyperbolic sine) of the values.
Send in column (9) is the number of unique individuals money is sent to via MPESA by the customer.
Paybill in column (10) is the number of paybill payments made over M-PESA.
PB Clients in column (11) is the number of unique organizations the individual has paid on M-PESA using the paybill service.
Bank Clients in column (12) is the number of unique bank accounts the customer transferred money from.
The specification in all columns is as per Eq. (1) in the paper with differential linear slopes on either side of the cutoff.

Table 2B
Balance in survey data.

	Non-Response	Demographics				Characteristics
	(1)	(2) Household head age	(3) Catholic	(4) Head education	(5) Spouse education	(6) Land owned
Bandwidth of −9 to 10						
Score cutoff	−0.003	0.870	−0.041	−0.104	0.064	−0.064
	[0.024]	[0.796]	[0.027]	[0.235]	[0.264]	[0.164]
Control mean	0.317	36.429	0.268	10.783	10.053	1.694
Observations	6000	3949	4136	3956	2711	4136
Bandwidth of −4 to 5						
Score cutoff	0.005	1.273	−0.017	0.160	0.413	0.016
	[0.035]	[1.169]	[0.040]	[0.344]	[0.385]	[0.250]
Control mean	0.314	36.376	0.284	10.820	10.054	1.639
Observations	3059	2023	2111	2028	1408	2111

Note: Robust standard errors in brackets.
In column (3), Catholic refers to whether the respondent is a Catholic.
In columns (4) and (5), Head Education and Spouse Education refer to the years of education of the household head and spouse, respectively.
In column (6), Land Owned refers to the total acres of land owned by the household.
The specification in all columns is as per Eq. (1) in the paper with differential linear slopes on either side of the cutoff.

completely different sample of individuals. For this, we obtained administrative data on a random sample of 10,000 M-Shwari customers who opened their accounts between January and March 2016 (a year after our sample opened their accounts) 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.

This sample is for all credit scores. Of these 10,000, there are 1468 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.[15] Table 1F contains the summary statistics on this separate sample and shows that the overall loan amount taken over this period is around 8200 KSh which is more than two and a half times the total loan amount taken by individuals within the RD bandwidth (around 3200 KSh).

Fig. 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 gray 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 Fig. 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 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, Fig. 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.

Fig. 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

[15] 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.

(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 and we see that the credit limits of those above and below the cutoff are not significantly different by October 2016. However, it is worth mentioning two caveats to this figure. First, the sample size is quite small as only 1474 individuals fit in the −9 to +10 bandwidth and credit limits only change every few months; hence, between January 2016 and October 2016, there are not that many changes in credit limits. The sample size with growing credit limits is even smaller so we are not powered to detect changes in credit limits for this sample. In addition, the RD design argues that those above and below the cutoff are indeed quite similar in their risk profiles and therefore it should not be surprising that there is a catch up in credit limits. However, those above the cutoff, relative to those below, have had access to the lending platform for longer (as seen in both figures), they have taken our more loans (as seen in Fig. 1E and Table 3A) and they have borrowed more than double the amount of money in total since they opened their accounts (see Table 3A). Ultimately, we think that is the evidence of a significant difference in accessibility to credit above and below the cutoff.

Finally, in Fig. 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 are very few loans where the loan size is below the credit limit.

4. 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:

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

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.

5. Results

5.1. 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 use of cell phones and M-PESA (variables that ultimately enter the credit score). All the variables that measure amounts are transformed using the inverse hyperbolic sine (henceforth arsinh). All variables, except for the 6 month and 1 month M-PESA balances do not change discontinuously around the cutoff, lending support to our empirical strategy (it should be noted that 6 month and 1 month M-PESA balances are *highly* correlated at 0.8). 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. As a reminder, "Top up" is the amount of airtime purchased (measured by the arsinh), "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 KSh 2 (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. As a reminder, "Value" is the value of total inflows (money received plus deposits made plus any bank transfers, measured by the arsinh), "1m/6m Bal" is the average daily balance in the person's account in the past 1 month/6 months (both measured as their arsinh), "Send" is the number of unique individuals money is sent to via M-PESA, "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. Our take away from Table 2A, is that we find no evidence of a systematic 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 from the survey data where we would expect balance. Survey non-response is reported in column (1) of Table 2B. While non-response to the phone survey is correlated with some observables (such as being male, being older, etc.) the key is that around the relevant cutoff there is no differential attrition (see Col 1 Table 2B). The attrition in our survey was largely due to phones being off and not being answered (this accounted for about 80% of attrition). There were very few actual refusals to participate in the survey. Given this, we are 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 480, or 4.8 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 descriptives of the household head, in particular age, religion, education, and spouse's education. Across these columns, we find no evidence that these are different around the cutoff. Finally, in column (6), we see no differential land ownership across the cutoff.

5.2. Outcomes

Next, we look at outcomes.[16] 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 Figs. 2A and 2B.

Fig. 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 span a much larger bandwidth compared to what we use for the rest of the paper. Fig. 2A shows in striking clarity the first stage of our design — individuals whose credit

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

Table 3A
First stage, access to M-Shwari, administrative data.

	Has loan	No of loans	Total loan amount		Average loan size		First loan default	Savings
	(1)	(2)	(3) Level	(4) Arsinh	(5) Level	(6) Arsinh	(7)	(8) Arsinh
Bandwidth of −9 to 10								
Score cutoff	0.243***	1.307***	1002.957**	1.886***	112.173***	1.540***	0.007	0.104
	[0.027]	[0.282]	[445.862]	[0.226]	[28.306]	[0.183]	[0.024]	[0.164]
Control mean	0.299	1.924	1512.596	2.413	166.307	1.980	0.066	1.000
Observations	5000	5000	5000	5000	5000	5000	2380	5000
Bandwidth of −4 to 5								
Score cutoff	0.192***	0.805*	575.272	1.399***	73.565*	1.158***	0.024	0.125
	[0.043]	[0.454]	[610.277]	[0.354]	[40.846]	[0.288]	[0.036]	[0.227]
Control mean	0.308	1.962	1549.290	2.467	169.070	2.038	0.065	1.000
Observations	2571	2571	2571	2571	2571	2571	1246	2842

Note: Robust standard errors in brackets.
All amounts are reported in Kenyan shillings, where the exchange rate was 100 KSh to the USD at the time of the survey in 2016.
Values in columns (4), (6) and (8) are transformed using arsinh (inverse hyperbolic sine).
The specification in all columns is as per Eq. (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).

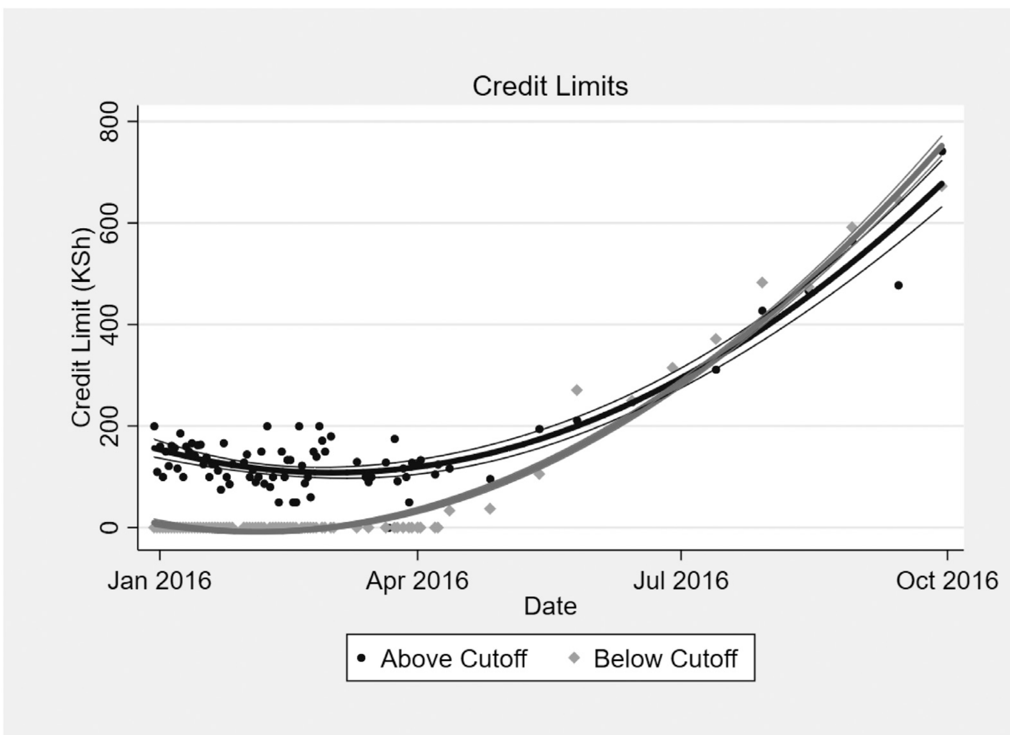

Fig. 1E. Credit Limit Evolution (Separate Sample, RD Bandwidth). Note: This is from a different sample of M-Shwari customers than the study sample (see text for details). Credit limits are reported in Kenyan shillings (KSh). The exchange rate is KSh 100 to the dollar.

scores fell above the cutoff are significantly more likely to have taken a loan, have more total loans, and have higher loan amounts.

Fig. 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%.[17] 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 Fig. 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 Fig. 2 shows similar results for the total number of loans).

Table 3 onwards show the regression analogs of the Figures, estimated according to Eq. (1) above. We also present these results for two sets of bandwidths to show that our results are not driven by choice of

[17] 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.

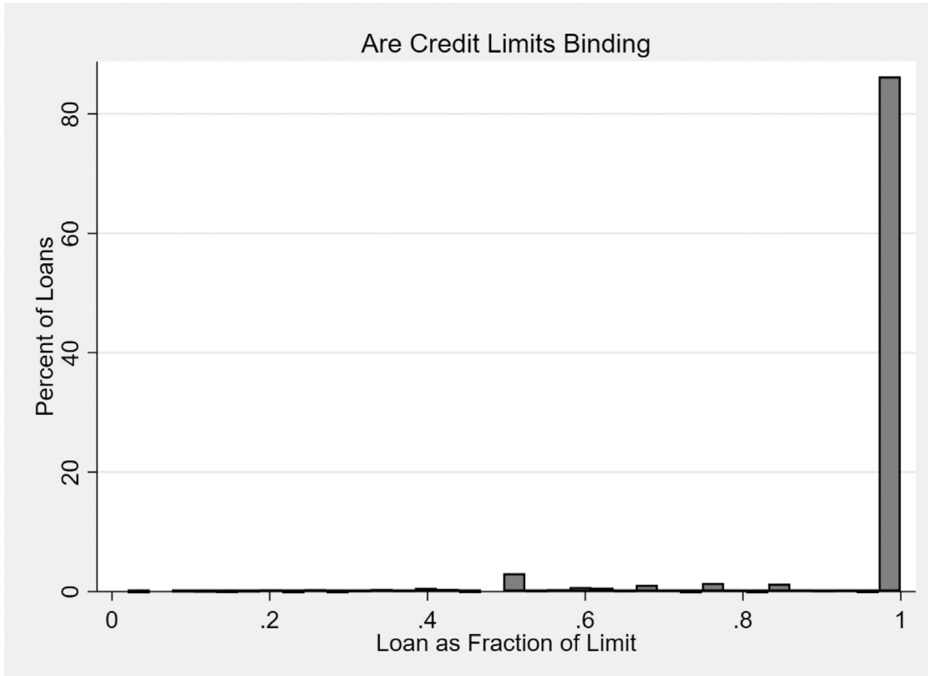

Fig. 1F. Loans and Credit Limits (Separate Sample, RD Bandwidth). Note: This is from a different sample of M-Shwari customers than the study sample (see text for details). This figure uses daily loan level data (conditional on borrowing) for this sample.

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 Fig. 2A (using the administrative data), but estimated over the same sample for whom we have survey data. Note that this is administrative data from M-Shwari and it therefore only covers loans from M-Shwari. 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 1000 KSh more in total loan amounts (the average in the control group is 1500 KSh, see Column (3)). To put these numbers in perspective, total *daily* consumption for households in our sample is around 560 KSh. Of course, the total loan amounts have long rights tails so in column (4) we also report the coefficients on the arsinh transform of total loan amounts — this shows between and 140% and 190% increase in the total amount borrowed by a household thanks to access to M-Shwari over this period.

In line with the idea that those with higher scores have higher credit limits, the average loan amounts borrowed by individuals above the cutoff are over twice that of those below the cutoff (see Columns (5) and (6)). 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. Finally, Column (8) shows that those eligible for the loans are not more likely to save in MShwari. While all individuals can save in their MShwari account the instant they open an account and regardless of the credit score they are assigned, one of the ways individuals can raise their credit limit (not their score which is fixed in time) is through savings. Hence, it is possible that savings could differ across the thresholds in either direction depending on what individuals know and how much they want to raise their credit limits. Empirically, we find no evidence of differential savings across the cutoff.

Table 3B shows the regression analogs of the graphs in Fig. 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)). 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. Looking at the effects on the levels of total debt, this is noisily estimated (column (3)), probably because of a large number of zeros as well as a long right tails in the amount of debt. When we use the arsinh transform (column (4)), indeed we see that the total amount of debt a household doubles across the cutoff.

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), again using the arsinh transform. These results show a large increase (more than doubling) in overall formal debt held by households. Note that the difference between total debt and formal debt is informal debt, which we look at more closely in Table 3C. 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 percent of household daily consumption). Column (6) shows no differential interest burden due to M-Shwari. Although the coefficients on the interest paid are not statistically significant, they are large in magnitude relative to the mean in the control. Note that interest paid is defined as the amount paid as a percent of total consumption over the comparable period. In absolute magnitude, the effects are still quite small, with the coefficient in the top panel of column (6) at a 0.06 percentage point increase in interest paid per unit of consumption. In that sense, the control mean itself is also quite small in magnitude. Finally, column (7) shows that those likely to access loans are not more likely to turn around and lend 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

Table 3B
First stage, access to credit.

	(1) Had any loan	(2) No of loans	(3) Total debt	(4) Total (Arsinh)	(5) Formal debt (Arsinh)	(6) Interest paid	(7) Gave loan
Bandwidth of −9 to 10							
Score Cutoff	0.106***	0.320***	1758.431	0.957***	1.145***	0.059	0.040
	[0.031]	[0.082]	[3684.916]	[0.295]	[0.291]	[0.042]	[0.028]
Sidak–Holm p-value	0.010	0.002	0.999	0.019	0.999	0.882	0.877
Control mean	0.455	0.766	14 622.736	4.018	3.505	0.162	0.293
Observations	4136	4109	4136	4136	4136	4080	4136
Bandwidth of −4 to 5							
Score cutoff	0.119***	0.377***	5705.199	1.101**	1.413***	0.069	0.051
	[0.045]	[0.124]	[5349.003]	[0.433]	[0.426]	[0.059]	[0.041]
Sidak–Holm p-value	0.125	0.041	0.939	0.163	0.939	0.939	0.935
Control mean	0.455	0.764	14 283.339	3.986	3.483	0.134	0.285
Observations	2111	2096	2111	2111	2111	2082	2111

Note: Robust standard errors in brackets.
Interest is reported as a percent of the 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 Eq. (1) in the paper with differential linear slopes on either side of the cutoff.

Table 3C
First stage, sources of credit.

	MShwari		Bank loan		MFI loan		SACCO loan		ROSCA loan		Informal loan	
	(1) Dummy	(2) Amount	(3) Dummy	(4) Amount	(5) Dummy	(6) Amount	(7) Dummy	(8) Amount	(9) Dummy	(10) Amount	(11) Dummy	(12) Amount
Bandwidth of −9 to 10												
Score cutoff	0.133***	0.958***	0.011	0.169	0.005	0.059	0.003	0.004	0.024*	0.231	0.001	0.018
	[0.028]	[0.217]	[0.015]	[0.160]	[0.008]	[0.088]	[0.012]	[0.140]	[0.014]	[0.142]	[0.015]	[0.143]
Sidak–Holm p-value	0.000	0.135	0.997	1.000	0.999	1.000	1.000	0.999	0.751	0.996	1.000	1.000
Control mean	0.210	1.603	0.057	0.555	0.019	0.220	0.043	0.454	0.054	0.521	0.067	0.613
Observations	4136	4136	4136	4136	4136	4136	4136	4136	4136	4136	4136	4136
Bandwidth of −4 to 5												
Score cutoff	0.126***	0.858***	0.026	0.307	0.014	0.153	0.018	0.148	0.032	0.323	−0.019	−0.166
	[0.041]	[0.322]	[0.022]	[0.229]	[0.011]	[0.127]	[0.019]	[0.214]	[0.022]	[0.218]	[0.022]	[0.212]
Sidak–Holm p-value	0.040	0.427	0.939	0.939	0.935	0.904	0.939	0.939	0.889	0.939	0.939	0.939
Control mean	0.214	1.633	0.054	0.497	0.017	0.192	0.041	0.451	0.053	0.515	0.064	0.591
Observations	2111	2111	2111	2111	2111	2111	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.
All amounts are measured as the arsinh (inverse hyperbolic sine) of the loan amount.
The specification in all columns is as per Eq. (1) in the paper with differential linear slopes on either side of the cutoff.

different potential bandwidths, we show more bandwidths in graphical form in Fig. 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 (3)-(10) examine formal sources of credit and it is clear when we compare column (1) and (2) to columns (3)-(10) that all the increase in loans that we saw in Table 3B is the result of M-Shwari. Note that odd numbered columns are all dummy variables for whether the household has had a loan from each of these sources, while even numbered columns examine the amount under each loan type (including zeros and using the arsinh transform). Columns (3), (5), and (7) show that there are no effects (statistically as well as in magnitude) on other forms of formal credit from banks, SACCOs, or MFI's. Column (9) shows a significant impact on ROSCAs (although the significance is only at the 10% level), but the direction is *positive*, i.e. people who have access to MShwari loans are more likely to also participate in ROSCA loans. However, note that all these other forms of formal credit have very low take up to begin with. Columns (11) and (12) examine 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 4 we report results for these outcomes. It is important to note that the samples used in Table 4 condition on households having faced a negative shock.[18] Hence, we are asking whether, conditional on facing a negative shock, households

[18] Measurement error in who reports a shock, and whether these shocks correlate with actual consumption or income losses is a legitimate concern here. Since most of our sample reports a negative shock, we do not have the variation to test whether these reported shocks correlate with actual consumption measures. However, from previous work on M-PESA (see Jack and Suri (2014)) we know that self-reported shocks correlate well (and negatively) with consumption.

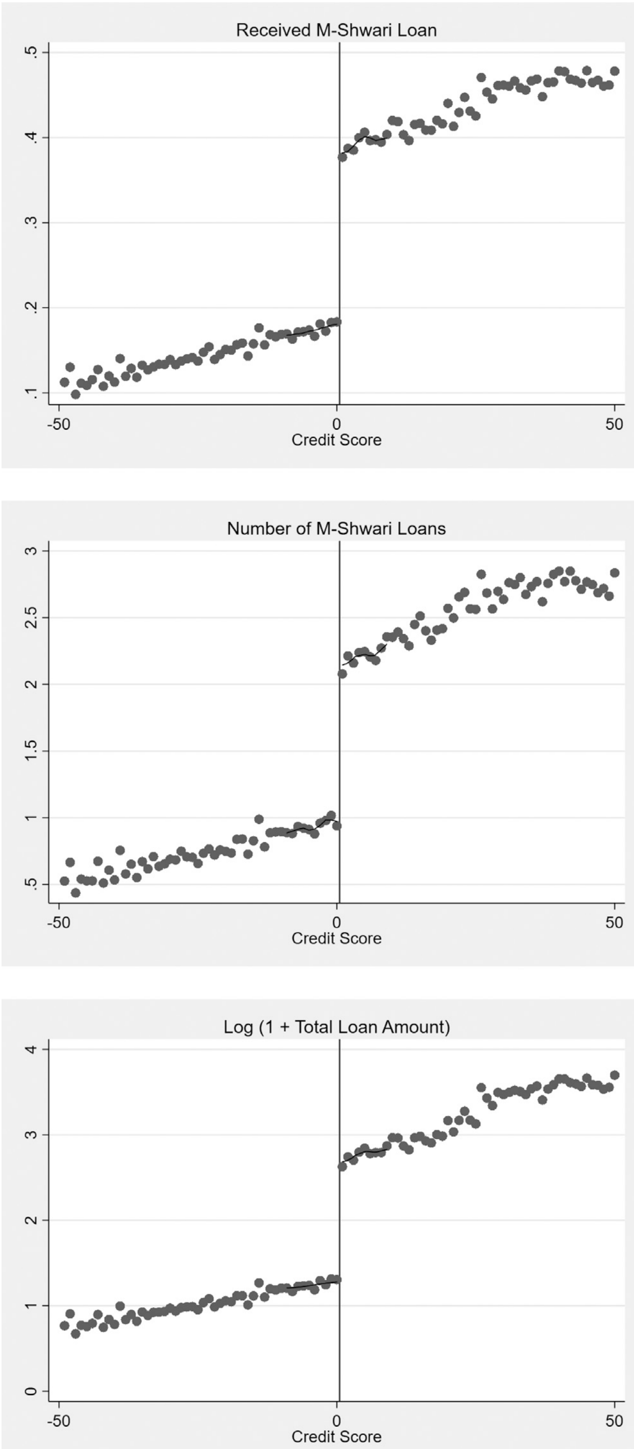

Fig. 2A. First Stage, Administrative Data. Note: The data covers all M-Shwari loans received in the 18 months prior to the sampling for the survey.

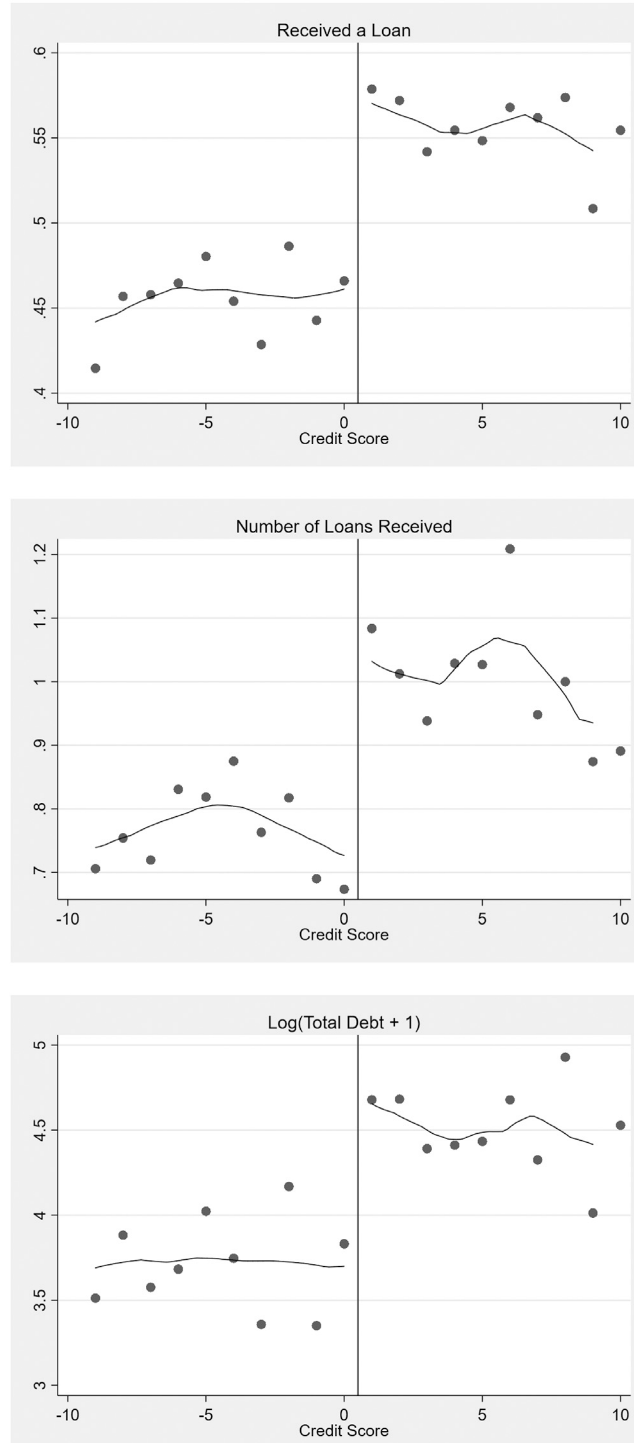

Fig. 2B. First Stage, Survey Data. Note: The data covers all loans received in the 2 years prior to the survey from all sources, not just M-Shwari.

are able to not cut back on spending in various categories. 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 economically small in magnitude. This coefficient is statistically sensitive to the bandwidth choice though the magnitude of the coefficient does not change. This is largely because the standard errors are almost fifty percent higher in the tighter bandwidth given the sample size is much smaller in the tighter bandwidth specification.

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 Column (3) we report the effects on the number of different types of expenses foregone and here, too, we see large negative effects (or improvements in resilience). In columns

Table 4
Resilience.

	Shock	Expenses foregone					Other adjustments		
	(1)	(2) Any	(3) Number	(4) Meals	(5) Medical	(6) Non-Food	(7) Child out of school	(8) Left job	(9) Sold assets
Bandwidth of −9 to 10									
Score cutoff	0.013	−0.063**	−0.115*	−0.045	−0.049*	−0.020	0.006	0.026	0.029
	[0.018]	[0.030]	[0.069]	[0.032]	[0.029]	[0.032]	[0.032]	[0.029]	[0.027]
Sidak–Holm p-value			0.960	0.960	0.960	1.000	1.000	0.995	1.000
Control mean	0.892	0.679	1.221	0.447	0.300	0.474	0.434	0.266	0.238
Observations	4136	3711	3711	3711	3711	3711	3711	3711	3711
Bandwidth of −4 to 5									
Score cutoff	0.006	−0.052	−0.209**	−0.095**	−0.081*	−0.033	0.080*	0.015	0.002
	[0.026]	[0.044]	[0.100]	[0.047]	[0.042]	[0.047]	[0.047]	[0.042]	[0.039]
Sidak–Holm p-value			0.582	0.482	0.740	0.985	0.959	0.985	0.985
Control mean	0.901	0.698	1.245	0.462	0.297	0.486	0.434	0.263	0.219
Observations	2111	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 specification in all columns is as per Eq. (1) in the paper with differential linear slopes on either side of the cutoff.

Table 5A
Main consumption results.

	Arsinh of expenditures				Dummy for any expenditures					
	(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	−0.016	0.102	−0.046	−0.040	0.058**	−0.046	−0.021	−0.025	−0.001	0.010
	[0.054]	[0.067]	[0.114]	[0.087]	[0.027]	[0.032]	[0.030]	[0.025]	[0.027]	[0.017]
Sidak–Holm p-value		0.817	0.998	0.996	0.817	0.986	0.999	0.999	1.000	1.000
Control mean	6.377	5.649	4.561	3.836	0.771	0.547	0.730	0.834	0.786	0.081
Observations	3711	3701	3701	3701	3701	3701	3701	3701	3701	3701
Bandwidth of −4 to 5										
Score cutoff	−0.009	0.184*	−0.132	−0.101	0.059	−0.045	−0.021	−0.057	0.005	−0.001
	[0.078]	[0.095]	[0.166]	[0.129]	[0.038]	[0.047]	[0.044]	[0.037]	[0.039]	[0.025]
Sidak–Holm p-value		0.389	0.995	0.998	0.818	0.995	0.998	0.995	0.998	0.998
Control mean	6.366	5.621	4.567	3.831	0.752	0.564	0.721	0.838	0.775	0.063
Observations	1913	1907	1907	1907	1907	1907	1907	1907	1907	1907

Note: Robust standard errors in brackets.
All specifications are for the subset of households that experienced negative shocks.
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 Eq. (1) in the paper with differential linear slopes on either side of the cutoff.

Table 5B
Consumption in levels of expenditures, winsorized at 10%.

	(1) Total	(2) Food	(3) Basics	(4) Airtime	(5) Education	(6) Health	(7) Clothing	(8) Assets	(9) Temptation goods
Bandwidth of −9 to 10									
Score cutoff	12.344	8.169	−2.888	−1.113	10.467**	−1.246	−1.240	1.555	2.464
	[22.148]	[5.520]	[4.521]	[1.870]	[4.074]	[1.215]	[4.236]	[2.564]	[1.647]
Sidak–Holm p-value		0.985	1.000	0.997	0.462	1.000	1.000	1.000	0.995
Control mean	610.589	161.277	80.554	34.692	45.625	11.190	52.506	27.185	16.820
Observations	3340	3331	3333	3472	3308	3332	3347	3334	3332
Bandwidth of −4 to 5									
Score cutoff	16.222	12.573	−2.617	−0.940	15.310**	0.037	−3.009	−0.616	0.537
	[32.754]	[8.012]	[6.692]	[2.752]	[6.090]	[1.745]	[6.157]	[3.817]	[2.447]
Sidak–Holm p-value		0.667	1.000	1.000	0.330	1.000	1.000	1.000	1.000
Control mean	611.801	161.714	81.546	34.097	44.415	11.755	50.991	27.889	16.451
Observations	1737	1732	1728	1790	1713	1714	1731	1725	1732

Note: Robust standard errors in brackets.
All specifications are for the subset of households that experienced negative shocks.
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 Eq. (1) in the paper with differential linear slopes on either side of the cutoff.

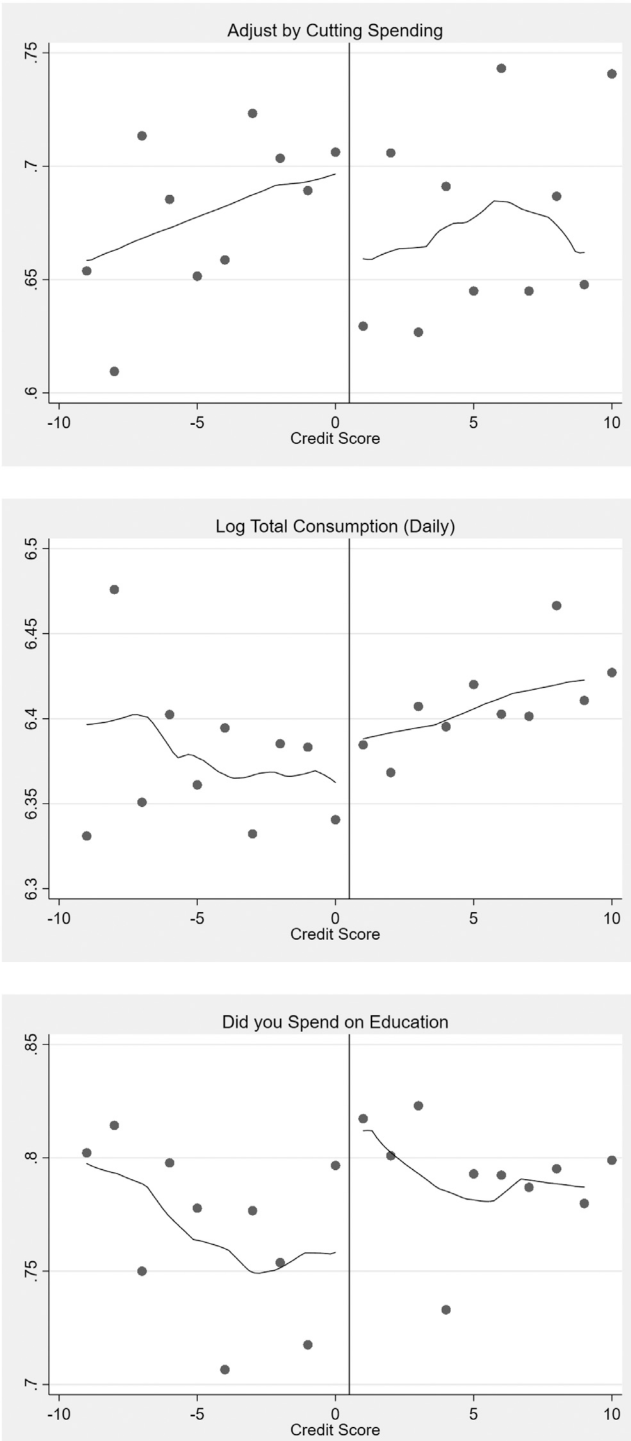

Fig. 3. Resilience and Expenditures. Note: The first panel shows survey data on whether the household cut expenses of any sort to deal with a negative shock. The second panel shows survey data on total daily household consumption (in logs). The third panel shows survey data on whether the household spent on education in the past year).

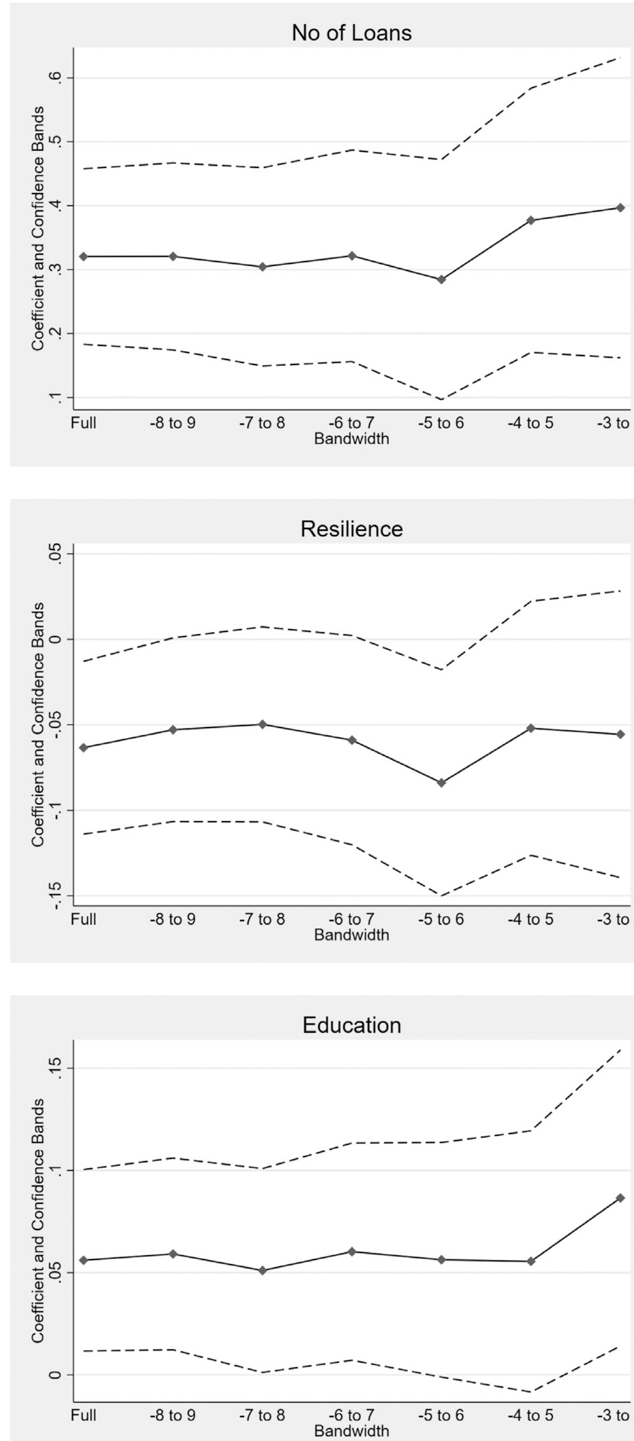

Fig. 4. Robustness to Bandwidth. Note: All three panels shows robustness of the estimated RD coefficient (from Eq. (1)) to varying bandwidths. The outcome in the first panel is the number of loans borrowed in the 2 years prior to the survey. The outcome in the second panel is whether the household cut expenses 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.

(4) through (6), 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 Fig. 3) and medical expenses (column (5)). 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.[19] 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. We do not find strong evidence for adjustments along these margins (most of the estimates are statistically insignificant and small in magnitude).

Table 5A 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[20] and expenditures on prepaid airtime for mobile phones. For these four columns, we use the arsinh transform. We chose these four outcomes to report levels on as over 90% of households spend on these items. Not only are the coefficients for these four columns statistically insignificant, their magnitudes are small. The remaining columns examine whether a household reports positive expenses along a range of consumption categories. We similarly find small and insignificant impacts on health (column (6)), clothing (column (7)), assets (column (8)), temptation good[21] expenditures (column (9)) and alcohol and cigarettes (columns (10)), we find a large and marginally statistically significant impact on education expenses (column (5)). We also test whether the education coefficient in Table 5A Column 6 is different from the coefficients on expenditures on health, clothing, assets, temptation goods and alcohol and tobacco. We can reject that the education coefficient is the same as health, clothing, and assets at the 5% level.

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 Fig. 3 (with robustness across bandwidths shown in the third panel of Fig. 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 mechanisms for health shocks when studying how M-PESA affects consumption smoothing. Their work on M-PESA shows that in response to a health shock, all households spend equally on health care, but those that do not have M-PESA source the money from other parts of their budget (food and non-food related expenses, which includes schooling). Those that have M-PESA do not make this adjustment as they receive money from friends and family on their phones.

Table 5B shows the impacts on the levels of consumption where we winsorize the consumption data. We exclude alcohol and tobacco consumption from Table 5B as less than 10% of the sample reports spending on these items. In addition, in the online Appendix, we show results for the non-winsorized consumption levels (see Appendix Table 1), for the 5% winsorized outcomes (see Appendix Table 2) as well as the inverse hyperbolic transformed consumption data for the continuous variables that are shown as dummy variables in Table 5A (see Appendix Table 3). Similarly, for Table 5B we can test whether the education coefficient is significantly different from the coefficients on all the other expenditure variables (except total consumption), and we find it is different (two at the 1% significance level, two at the 5% level and two at the 10% level) from expenditures on basics, airtime, health, clothing, assets and temptation goods (i.e. everything except food consumption).

In Appendix Tables 1 and 2, we can also see the education coefficient is larger than the others (even though it is not statistically significant). However, we should point out that the education coefficient in Table 5B is not statistically different from either of those in Appendix Tables 1 and 2. If we test whether the education coefficient is different from the others, we find that it is not significantly different from any of the other expenditure variables in both Appendix Tables 1 and 2. In Appendix Table 3 (the inverse hyperbolic transformation), the coefficient on education is large in magnitude (25%) and it is significantly different from the coefficients on expenditures on food, basics and airtime (all reported in Table 5), as well as the coefficients on expenditures on clothing and assets (reported in Appendix Table 3).

Just to give some sense of magnitude of the education coefficient in Table 5B, not just as an effect size but in the magnitude of the value, the coefficient in the top panel is KSh 10 per day. This amounts to an increase in annual education consumption of approximately KSh 3600 per year. As a benchmark, if we look at the results in Jack and Suri (2014), in response to a shock, M-PESA users receive about KSh 2000 extra (relative to non-users) in remittances over a year to help them smooth risk. So the increase in annual education is quite large relative to that. If we use the coefficient in Appendix Table 1, the increase in education expenditure would be KSh 1800 per year, which is still quite large. Note that the results in Jack and Suri (2014) are for a sample that almost national and so the average consumption levels are likely to be lower in their survey (our sample is richer than the average as we show in Tables 1D and 1E).

Finally, Table 6 examines whether increased access to loans affects the financial and real assets of the household to which the M-Shwari loan-eligible individual belonged. Again for all the variables that are amounts (amounts of savings or value of assets), we report effects on the arsinh transform of the relevant variable. We find that such households do not seem to have increased savings along any of these measures. The number of savings instruments used is higher (Column (1)) but total savings (whether measured as current savings or savings in the last month) are not significantly higher, though the coefficient on current balances is larger and the magnitude is economically large. The effect on total savings (even though this is not statistically significant) could be the result of people increasing savings in M-Shwari to build up their credit score. In Columns (6) and (7) we examine the impacts on the value of total assets and the value of productive assets.[22] We find no statistically significant impacts on these measures of assets, though the coefficients are sensitive to the bandwidth and the magnitudes are sometimes not small.

6. 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

[19] While M-Shwari loans are typically repaid within a month, it is possible that households facing shocks repay over a longer horizon. The consequences of non-repayment are fairly severe only after 4 months of non-repayment.

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

[21] 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).

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

Table 6
Assets (Financial and Real).

	Savings instruments	Savings last month		Savings current balance		Arsinh asset value	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number used	Any	Amount	Any	Amount	Total	Productive
Bandwidth of −9 to 10							
Score cutoff	0.184*	0.007	0.047	0.011	0.295	−0.165	0.005
	[0.107]	[0.023]	[0.236]	[0.029]	[0.292]	[0.134]	[0.158]
Sidak–Holm p-value	0.934	1.000	1.000	1.000	0.999	0.996	1.000
Control mean	3.689	0.829	7.467	0.652	5.740	11.467	10.046
Observations	4136	4136	3930	4136	3930	4136	4136
Bandwidth of −4 to 5							
Score cutoff	0.272*	0.018	0.227	0.053	0.818*	0.209	0.268
	[0.157]	[0.034]	[0.345]	[0.043]	[0.425]	[0.187]	[0.218]
Sidak–Holm p-value	0.934	1.000	1.000	1.000	0.999	0.996	1.000
Control mean	3.676	0.831	7.477	0.648	5.672	11.465	10.037
Observations	2111	2111	2002	2111	2012	2111	2111

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.
Values in columns (3), (5), (6) and (7) are transformed using arsinh (inverse hyperbolic sine).
The specification in all columns is as per Eq. (1) in the paper with differential linear slopes on either side of the cutoff.

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 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 Jack and Suri (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.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2021.102697.

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