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Abstract

Digital credit has expanded rapidly in Africa, mostly in the form of short-term, high-interest loans offered via mobile money. Loan terms are often opaque and consumer financial literacy is low, providing opportunities for predatory lending. A regression discontinuity analysis shows no negative effect of access to digital loans on financial well-being, but the majority of borrowers fail to repay on time and incur high late fees. We randomize exposure to a short phone-based financial literacy intervention. The intervention improved knowledge and marginally improved loan repayment but *increased* loan demand, increasing overall default risk.

JEL classification: D14, O12, O16
Keywords: financial literacy, predatory lending, regression discontinuity, field experiment

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1 Introduction

Digital credit has exploded in popularity across the world in recent years. Digital loans are disbursed and repaid electronically, and can be distinguished from conventional credit by being "instant, automated, and remote" (Chen and Mazer 2016); that is, loans do not require in-person interaction, and decisions are made by an algorithm rather than by a loan officer. Digital credit is also typically associated with the use of non-traditional data for scoring, such as mobile money transaction history.

In Sub-Saharan Africa, the most common form of digital credit currently being offered are consumer loans disbursed via mobile money platforms. Typically, these loans are short-term (most loans are due within a month, and are often due after only a week or two), for small amounts of money, and feature high effective interest rates well over 100% APR (when annualized). The market for digital credit has vastly expanded in recent years, especially in early adopter countries like Kenya where millions of people have taken out loans.[1]

While the enormous demand for digital credit shows that millions of consumers have a need for a source of easy liquidity, a major cause for concern is that many consumers are not aware of loan terms and many end up repaying late (incurring fees), or defaulting (hurting their future ability to borrow).[2] There have been a number of news stories of harmful lending practices, focusing on issues like debt traps and exploitative lending practices, both in and outside of Africa.[3,4]

Despite the growth of this market, there is little rigorous evidence on the effect of digital credit as currently offered in Africa. In this paper, we report results from two analyses we conduct on a digital credit product called *Kutchova* which is offered by the mobile network operator (MNO) Airtel in Malawi. Airtel is the bigger of the two dominant MNOs in Malawi with a subscriber base of approximately 4.8 million users, in a country with a population of approximately 18.5 million. *Kutchova* is similar to digital credit products offered on mobile

[1]See Ogada and Hammond (2021), Francis et al. (2017), and Robinson et al. (2021) for reviews.

[2]See Johnen et al. (2021) for a discussion of credit bureau blacklisting in Kenya.

[3]For Kenya, see for example "Perpetual Debt in the Silicon Savannah", Boston Review 2019; "Kenya is preparing to crack down on a flood of high-interest loan apps", Quartz Africa 2021; "It's Time to Protect Kenyans from a Digital Lending Laboratory", Center for Financial Inclusion 2020.

[4]In India, unlicensed lending apps employed predatory lending practices, including aggressive debt collection tactics. The crisis was serious enough that the Reserve Bank of India banned many such apps from the Google Play Store. See "Downloading a debt trap", Indian Express 2021 for more details.

money networks in other African countries. Loans are issued by a bank, and disbursements and repayments are transacted on Airtel's mobile money network. The loans feature a 10% facilitation fee and are due in 15 days. One difference compared to other products is that *Kutchova* charges sizeable late fees (up to 22.5% if the loan is not repaid after 30 days) that far exceed those reported by other digital credit providers and that are not transparently disclosed. Eligibility for loans is determined by a third-party credit scoring firm, which scores based on mobile money usage. The average loan size is small, only a few dollars. Because people take out loans repeatedly, however, the total amount of credit does accumulate: the average user takes out about $18 of loans over the 9 months of data we observe, and some take out much more. Borrowers report using these loans for a range of purposes, but the three most common uses are to buy airtime, food, and electricity. Default is common, as is late payment: across all the loans in our sample, 11% are never paid back at all, 4% are paid back partially, and 47% are fully paid back, but late. Only 38% are paid back fully on time.

We conduct two separate empirical analyses, taking place in 2019-20, timed to coincide with the relaunch of the product after a dormant period.[5] We conduct (1) a regression discontinuity design (RDD) analysis to examine impacts on borrower outcomes, and (2) a randomized intervention to examine the role of a low-touch, low-cost financial literacy intervention on take-up and repayment of loans.

In the RDD analysis, we compare users just above and below the credit score cutoff to qualify for loans. Despite the high interest rate, we find robust demand for digital credit: 34% of barely-eligible borrowers took out at least one loan in the 9 months that followed the product launch. The total amount borrowed is small, however: average borrowing at the threshold is around $2 over those 9 months, which corresponds to $5.7 among those who borrowed at least once.[6] Descriptive evidence suggests that in the absence of these loans, most people would not have had access to alternative sources of credit. We examine several outcomes, including self-reported financial well-being, food security, and savings. We find a positive and statistically significant

[5] Until the end of 2020, *Kutchova* was the only digital mobile money product offered by an MNO in Malawi, and so consumers who were ineligible for *Kutchova* would not have access to other digital loans. There are several products which provide airtime on credit, however, at similar terms.

[6] This first stage is somewhat larger than Suri et al. (2021) on the extensive margin but smaller in value. In that paper, the RD estimate is 0.24 on the extensive margin but about $10 in total credit (implying about $40 worth of loans for those who borrow at least once). Another contextual difference is that the control in our study had no alternative source of credit, unlike Kenya.

increase of 12 percentage points (equivalent to 23%, on a base of 55% for those just below the eligibility threshold) on a subjective measure of financial well-being ("are you satisfied with your financial wellbeing?"), and mostly positive but insignificant impacts on other subjective measures of financial security. We do not find significant effects on financial debt or reported savings, though confidence intervals are large. We also do not find any evidence that these loans were used to deal with specific shocks.

While there exists demand for digital credit, and our RDD analysis shows no significant harmful effects on average, many borrowers pay loans back late, incurring very large fees and raising the possibility that financial literacy training may be important. To shed light on this, we designed and implemented a financial literacy "interactive voice response" (IVR) module, which respondents could participate in over the phone. The module lasted about 15 minutes, and mentioned the interest rate, due date, and presence of late fees. It also included a discussion of how the cost of borrowing adds up over time, especially relative to using savings. The module noted the possibility that loans could be reported to the credit bureau. This was accompanied by three text messages about the loan terms. We compare this intervention to three other groups: a "placebo group" that took part in a shorter IVR module which provided no information but was intended to make *Kutchova* salient, a group which received only the text messages, and a pure control group.

The financial literacy intervention was successful at increasing knowledge about the types of fees and other costs/risks associated with *Kutchova* loans. However, an event study analysis exploiting the fact that the intervention was rolled out randomly over several days shows that it did not have any immediate impact on repayment of outstanding loans. In the months that followed, the literacy intervention *increased* loan demand, both on the extensive and intensive margins. Individuals sampled for the financial literacy intervention were 4 percentage points more likely to take up a loan (compared to 25% in the control group) in the 3 months after treatment. In the medium run (after 3-9 months), they took on 0.12 more loans (an 11% increase). The finding that an intervention that increases awareness of costs and risks only makes the product more attractive could potentially be explained by ambiguity aversion (Bryan 2019). Most likely, it also reflects the difficulty of accessing credit in a country like Malawi, where interest rates on other loans (such as loans from savings groups) are also quite high. In fact, many respondents reported that the financial literacy module taught them that

Kutchova, if repaid on time, was *less* expensive than they had expected. At the end of the IVR module, participants were asked what source of cash they would prefer "next time you need cash rapidly". The overwhelming majority said *Kutchova* (88%).

The Financial Literacy treatment warned of the ratcheting of costs if one repays late. As such, one intended effect was to deter late repayment. While there is no effect on outstanding loans at the time of treatment, we find a small impact on repayment for loans taken after the intervention: treatment individuals were 1.6 percentage points (on a base of 39.2%) more likely to repay new loans on time, and 1.1 percentage points less likely to pay back nothing (on a base of 11.2%). However, given the increase in loans taken, over the 9 months after treatment, newly eligible borrowers were 1.7 percentage points more likely to have defaulted on their last loan (on a base of 14.9%). For the lender, financial literacy is beneficial – because it increases demand without increasing the loan-level probability of default. For the borrowers, the effects are unclear, and depend on the consequences of ultimately defaulting. At this time, consequences of default seem limited to being barred from future *Kutchova* borrowing. While Airtel official communication with users includes the possibility that they will report defaults to the credit bureau, in private communication Airtel has repeatedly stated that they have not reported anyone to date. But if/when the lender starts reporting defaults to credit bureaus, consequences for customers could worsen (as is the case in other countries such as Kenya).

While our RCT results suggest that a low-touch, low-cost financial literacy campaign can be profitable for the lender, we also find evidence that aggressively marketing the product (without information) can backfire. We document a sudden surge in demand for *Kutchova* on a specific day early on in the relaunch, which is indicative of a mass, SMS-based marketing campaign. We find that loans taken during the surge are significantly less likely to have been repaid; they generate a 10 percent loss for the lender on average. This suggests that the "ease" of digital credit for borrowers is a double-edged sword. These results mirror those of Burlando et al. (2021), who find that the speed with which internet-based digital loans can be obtained in Mexico is associated with lower loan repayment.

For each analysis, we designed the study to separately analyze effects for men and for women. Indeed, in Malawi like elsewhere (i.e., Demirgüç-Kunt et al. 2018), gender is a strong correlate of baseline financial access as well as phone and mobile money access: within Airtel, only 41% of users, and 36% of those eligible for digital loans, are women. While many hope that digital financial services (DFS) will reduce gender inequity (because the algorithms are blind, and because reducing transaction costs could level the playing field – see for example Islam and Muzi 2020), underlying gender differences in access to the data generating the algorithms (in this case, a mobile money account) may undo the promise of DFS.[7] Interestingly, we find minimal differences by gender. Both the estimated effect of access in the RDD, and the impacts of the financial literacy training, are statistically indistinguishable between men and women.

This paper is related to several strands of the literature. First, our paper is related to a literature examining the effects of short-term, high-interest rate loans. In the United States context, the picture is mixed. Several studies show positive effects of high-interest loans, including Morse (2011) who shows a positive effect of payday loans on mitigating a natural disaster, and Zinman (2010) who shows negative effects of interest rate caps in Oregon. But others show lasting negative effects, such as Skiba and Tobacman (2019) who find evidence that payday loans cause bankruptcy and Melzer (2011) who finds that payday loan access leads to negative effects on the borrower's later ability to pay bills. Outside the United States, Angelucci et al. (2015) find null effects of Compartamos loans in Mexico and Karlan and Zinman (2010) find positive effects of high-interest loans in South Africa. More directly, our paper is closely related to two recent papers on the effect of digital credit in Africa. Suri et al. (2021) find that the *M-Shwari* credit product improved households' ability to cope with shocks in Kenya, while a study contemporary to ours, Björkegren et al. (2021), find no evidence of major positive or negative effects of a smartphone-based digital lending app in Nigeria.

Second, our paper contributes to a literature, so far mostly US-based, showing that many consumers are poorly informed about costs of financial services, particularly "shrouded fees" such as late or overdraft fees.[8] Indeed, we also find that many borrowers pay extra fees by

[7]It is also possible that women are differentially impacted by misconduct in the form of overcharges by mobile money agents at the time they withdraw cash from their mobile money account, as found in Ghana (Annan 2019). There is also a concern that algorithms themselves could implicitly gender discriminate (i.e. Caliskan et al. 2017, Obermeyer et al. 2019). For a prominent example, see the discussion around gender bias with the Apple Credit Card: "Apple Card Investigated After Gender Discrimination Complaints", New York Times 2019.

[8]Stango and Zinman (2016) show that consumers differentially shop for interest rates, suggesting dispersion in access to information, while Stango and Zinman (2009) shows systematic mistakes in financing credit card debt in the US. Outside the US, Alan et al. (2018) provide experimental evidence from Turkey suggesting that consumers pay too little attention to overdraft costs. On the flip side, Allcott et al. (2021) estimate that many payday loan borrowers correctly estimate their chances of repaying loans, and that banning payday lending would reduce welfare. See Garz et al. (2020) for a recent review.

paying back fully but late. The most closely related study to ours is Bertrand and Morse (2011), which is a field experiment in which borrowers from a payday lender were informed of loan terms. In that study, this information caused borrowers to reduce their demand.[9] By contrast, in the Malawian context in which cheap credit options are almost nonexistent, we find the opposite: warnings about loan costs and default risk increased loan demand.

The specific context in which these findings obtain is important to keep in mind. Loan sizes are very small at present, in part because default is common (during our sample period, 15% of loans are not repaid in full). The product is only profitable because about half of loans are paid back fully but late, and charged extraordinarily high late fees. What's more, these late fees are not properly communicated to borrowers in advance of their first loan. The Terms and Conditions available to borrowers in advance of the loan request are inaccurate, stating a late fee of 2.5% instead of the fee actually charged (12.5%).[10] An ex post calculation of profits with only a 2.5% late fee reveals that the lender would lose money at the contracted-upon fee. The lack of transparency about loan terms, including with our research team, which discovered that the true fee was 12.5% only once we obtained the administrative loan data, raises serious concerns about the potential for further predatory behavior by the lender. As it is, negative impacts are limited by the size of the loans, but the lack of transparency and lack of knowledge among borrowers strongly suggests the need for consumer protections such as mandatory disclosure laws.

The remainder of the paper proceeds as follows. Section 2 provides the background on the digital product considered and the study context. Section 3 presents the RDD analysis, while Section 4 presents the RCT results. Section 5 discusses heterogeneity. Section 6 concludes.

[9] In a different context, Stango and Zinman (2011) show how truth in lending laws lower gaps in rates paid by more- and less-informed consumers.

[10] The terms and conditions are also only available on a website (see `https://airtel.mw/kutchova-T-and-C` and Figure A1), itself hard to access for users with a feature phone.

2 Background and context

2.1 Airtel Malawi's *Kutchova* Product

This paper evaluates a digital credit product known as *Kutchova*, which is offered on the mobile money network of the telecommunications company Airtel Malawi. Airtel is the largest telephone company in Malawi: at the time of this project, Airtel had approximately 4.8 million cellular customers, about 2.5 million of which have a linked mobile money account.

Our project takes place around the relaunch of the product in July 2019.[11] Loans are backed by FDH Bank, and are for small sums of money, usually just a few US dollars. Loans are technically for 7 days but jave an 8-day grace period, so in practice they are due after 15 days (i.e., if one borrows at 1:04pm on a given day, the loan is due at exactly 1:04pm 15 days later). Until the loan is repaid in full, no other loan can be taken on the *Kutchova* platform. As with most MNO digital credit products, there is no official interest rate; instead, there is a facilitation fee of 10%. In addition, customers are charged standard mobile money cash-out fees when they withdraw the loan (which are substantial – the fee for a 1,000 Malawian Kwacha withdrawal is 8%). There is a late fee of 12.5% levied if the loan is not repaid after 15 days, and a second late fee of 10% is applied after another 15 days have elapsed. If the borrower has not repaid on the due date, the lender attempts "auto recovery", i.e., automatic withdrawal from the borrower's mobile money account. When that happens, borrowers are charged the late fee.

The details of the late fee are not clearly disclosed to customers prior to their borrowing. The official Terms and Conditions provided by Airtel on their website and in fliers is that a late fee of 2.5% is charged every 15 days (see Figure A1). Additionally, the mobile interface used to request the loan does not mention late fees anywhere (Figure A2). However, customers who do borrow receive a warning 22 hours before the due time telling them that the late fee is 12.5% (Figure A3). Figure 3 shows that in the administrative data we obtained from Airtel, the total fee for users that fully paid back the loan on time is exactly 10%; for those users who repay fully the day *after* the due date, the total fee is 10+12.5=22.5%; and for those that repay fully at least 15 days late the fee is 10+12.5+10=32.5% (this is the maximum fee observed in the data; we observe it applied to 27% of all loans). After 45 days, the loan is considered in

[11] *Kutchova* had previously been launched in 2016 to approximately 373,000 eligible customers, of which 32% took out a loan. The product was suspended, however, due to liquidity issues with the lender.

default.

The extraordinarily high late fees we observe far exceed those reported by other digital credit providers,[12] and, as mentioned above, are not transparently disclosed. Prior to borrowing, customers do not have any way to know about the 12.5% fee (unless they borrowed before, had not repaid within 14 days and hence received an SMS warning). We (the research team) discovered that the true late fee was 12.5% only once we obtained the administrative loan data.

There is limited recourse for the lender if loans are not repaid. The lender could report delinquent borrowers to credit bureaus, but our understanding is that the lender does not do this.[13] Airtel reports that its main recourse is simply to exclude delinquent borrowers from future loan cycles. Such exclusion is indeed costly because, while customers can in principle buy a new SIM card and mobile money account, they must also restart a transaction history (and in fact, must wait a minimum of 6 months to regain eligibility – see next section). There may also be some limits on an individual's ability to do this given that Malawi has a national biometric ID system and now mandates "Know Your Customer" (KYC) registration.

Figure 1 shows the total number of loans taken weekly from the time of the relaunch in early July 2019 until May 2020. Demand appears fairly steady at around 1,000 loans per week throughout our study period. However, there is one major exception: over 2,000 loans were taken out on a single day (July 23, 2019), and close to 1,000 loans were taken out the following day, July 24. We attribute this large increase to a likely marketing campaign by Airtel on that day. We will be able to exploit this surge in take-up to understand whether aggressive marketing by the lender is profitable at the expense of borrowers (i.e., inducing some individuals to borrow who end up paying late fees). Figure 1 also shows that on-time repayment occurs for only about 38% of the loans. Overall, the product seems profitable for the lender, with the share of the principal repaid being over 100% on average, suggesting that fees charged to those who do repay more than compensate for those who default.

Figure A4 shows some statistics on what *Kutchova* is used for, as reported by borrowers (this data comes from a phone survey of respondents, which we will discuss in more detail below). There is a lot of heterogeneity: while 29% of people use loans for airtime, 20% use them for

[12]See Robinson et al. 2021 for a tabulation of fees on some other digital products.

[13]There are multiple private credit bureaus operating in Malawi such as Credit Data Malawi, CRB Africa, and TransUnion. As of August 2021, Airtel customer service representatives continue to state that they do not actually report people, though they do threaten delinquent borrowers with reporting.

food, and a minority for other consumption purposes. About 20% use loans for business or agriculture (somewhat surprisingly given how small they are), and only a small minority of people use loans for emergencies (about 2.7% of the sample use them for medical emergencies).

2.2 Credit Scoring and User Characteristics

While the research team was not involved in the actual credit scoring and does not know the algorithm which was used, we were in touch with Airtel and the credit scoring firm during the scoring process and these partners were willing to share some broad details. To be eligible, mobile money users had to have had an account for at least 6 months. It is our understanding that scoring was done using only mobile money transactions, and this data was not linked to other databases held by Airtel or any other firm. To our knowledge, it is not even linked to cellular airtime usage, or history of digital *airtime* loans (*Kutapa*). It is also our understanding that credit scoring is based on measures of recent mobile money usage such as values of transfers sent and received.

In the July 2019 relaunch, all 590,000 Airtel customers who had not previously borrowed from *Kutchova* but met the basic criteria (i.e., they had been active mobile money users for at least 6 months) were given a "predicted profitability" value. This profitability prediction mapped into a discrete credit score (between 374 and 912). Those with a score of 834 or above (around 44,000 users), were deemed eligible to take out a loan.[14] Airtel decided to begin lending with small loans: The entry-level loan was for MWK 1,000 (equivalent to about $1.4 USD), and about 66% of those eligible were given the MWK 1,000 credit limit.[15] MWK 1,000 is enough to pay for some daily expenses: for example, in Lilongwe a kilogram of maize flour, rice, or sugar, or a liter of diesel or paraffin costs about MWK 1,000, malaria treatment costs about MWK 1,200, and painkillers cost about MWK 300. Other expenses, such as major medical expenses or funerals, cost much more.

When Airtel relaunched the product in July 2019, they considered two groups: existing users who had borrowed from *Kutchova* prior to 2019, and new users. All eligible users were further classified into sub-groups. Existing users were split into three equal size groups labeled E1, E2

[14] A target number of 50,000 eligible customers (around 6,000 prior customers and 44,000 newly eligible) was chosen based on liquidity of the partner bank, and this is what determined the threshold score for eligibility.

[15] The other limits of MWK 2,000, 3,000, 4,000, 5,000, and 10,000 concerned only 16.5%, 11%, 4.1%, 1.7% and 0.8% of the sample, respectively.

and E3, and new users were split into four groups (N1, N2, N3 and N4). The July relaunch was planned to be gradual, with groups E1 and N1 scheduled to become eligible the first week of July, groups E2 and N2 the second week of July, and groups E3/N3 and N4 the third and fourth week, respectively. Figure A5 shows that in practice, only groups E1, N1, E2, and N2 (just under 27,000 users in total), actually got access to Kutchova in 2019—the rollout never reached groups N3, E3, and N4 due to limited liquidity.

Table 1 presents summary statistics on the entire sample of mobile money users active in the 3 months prior to credit scoring (January-March 2019) who either were eligible for scoring (Columns 1-3) or were existing *Kutchova* users in groups E1 and E2, and on the subset of users eligible for *Kutchova* during the 2019 relaunch (i.e, they received a credit score of 834 or above, or were previous Kutchova customers) (Columns 4-6). Groups N3, N4 and E3 are excluded from the table as they were eventually excluded from the relaunch. The sample is relatively young (68% of women and 64% of men are less than 40), and less than 6% are over 60. We observe a dramatic gender imbalance: only 41% of mobile money users are female. While men are more likely to own phones and use mobile money throughout the world, this gap is on the high end globally.[16] Panel B shows information on mobile money transactions for the 3 months prior to credit scoring (January-March 2019). Usage is fairly modest on average: the average user made only 3.8 transactions over these 3 months, for a total value of less than US$10. Women transact somewhat smaller sums ($9.6 vs. $9.9).

Turning to *Kutchova* access, the gender gap is even more pronounced. Women are less likely to be eligible: 1.73% of women are eligible, compared to 2.18% of men. This ultimately translates to only 36% of *Kutchova*-eligible individuals being women (Columns 4-6). Aside from the gender gap, *Kutchova* eligibles transact much more: 18 transactions on average across 3 months, compared to less than 4 transactions for the average mobile money user.

2.3 Loan Usage and Repayment

Figure 2 shows the sharp discontinuity in eligibility for Kutchova at the credit score threshold of 834. Only a handful of individuals with a score below the threshold show up in the admin-

[16]This gap is much larger than mobile money ownership statistics in the 2017 Findex (Demirgüç-Kunt et al. 2018) for Malawi, which shows a gap of only 2.3 percentage points in Malawi. Across all of Sub-Saharan Africa, the gap is reported as only 3.1 percentage points (21.3% for women vs. 24.4% for men).

istrative dataset as having been granted eligibility (i.e., we observe them taking up a loan). Among those above the threshold, take-up is around 44%. Panel C of Table 1 shows statistics on loan usage. Here we include both new and existing borrowers. Forty five percent of eligible men and 43% of eligible women took up a loan (the difference is statistically significant, with a p-value of 0.010). The average borrower takes out over 4 loans totaling about $14 for women and $20 for men (p-value ≤ 0.001).

The bottom of Table 1 Panel C shows statistics on loan-level information. Indicative of high default, only about 105% of the amount loaned is paid back, lower than the official amount owed of 110% (full principal + 10% facilitation fee). There is heterogeneity among loan types: only 38% are paid back on time fully, another 47% are paid back fully late, 4% are paid back in part, and 11% are not paid back at all. Women are more likely to not pay back at all and less likely to repay back on time. On average, loans to women have a lower return for the lender.

Figure 3 shows that a large fraction of loans are repaid the day before the due date. This is likely thanks to the SMS that borrowers receive within 24 hours of the due time, informing them of the exact due time and of the 12.5% penalty fee. The figure also shows that a surprisingly large fractions of loans are repaid fully on the due date, but *late*–after the due time. This is, to the best of our knowledge, due to the auto-recovery feature: when a loan is due, Airtel charges the 12.5% fee on the amount due and then attempts to recover the amount due by taking money from the user's mobile money account. Users who have enough funds on their mobile money account to repay all or part of their loan would save substantial late fees if they transferred the funds themselves on time, instead of letting Airtel do it on their behalf a few hours *after* the deadline. Figure A6 zooms in on repayment behavior at the hourly level, and shows the aberrant "just-after-the-deadline" repayment at play for all deadlines (when the loan is first due after 15 days, when the second late penalty of 10% fee kicks in after 30 days, and when the loan becomes "in default" after 45 days).

How truly predictive of repayment behavior are the credit scores created by the third-party for newly eligible borrowers? Figure A7 plots the average net revenue for the lender against the credit score. We bin the credit scores into 20 quantiles and show a quadratic fit, separately by gender. The top panel includes the full range of scores from the eligibility threshold (834) to the 95th percentile. The bottom panel zooms in on the scores close to the eligibility threshold, the bandwidth used for the RDD analysis below (scores between 834 and 842). Within the small bandwidth near the threshold, the scores seem to be predictive of the revenue for the bank, for both female and male borrowers. However, further away from the threshold, the scores for females do not seem to be predictive. Our understanding is that the third-party creating the score did not have access to the gender of the user at the time they created their algorithm.

2.4 Financial Access in Malawi

In surveys discussed below, we collected detailed information on access to credit (digital and non-digital), which we present here for context. Results are presented in Table 2. We asked about all sources of credit over the 3 months prior to the survey, and we present information on the 6 largest categories of loans: digital airtime loans, loans from friends and family, Voluntary Savings and Loan Associations (VSLAs), MFIs/banks, Rotating Savings and Credit Associations (ROSCAs), and moneylenders. We present results in order of frequency of usage.

Digital airtime loans are popular: 57% of respondents took out at least one loan in the past 3 months, and conditional on taking out a loan, the average number of loans is 6.5. These loans are small, and have similar terms to digital credit (the average reported interest rate is about 11% and is due in 1-2 weeks).

Interest rates on other types of credit are similarly expensive. For example, 10% of respondents have taken out loans from VSLAs over the past 3 months, even though the rates on VSLA loans are over 20% over about 2 months, equivalent to 200% APR. About 1% of people took out loans from moneylenders, at about a 36% interest rate over 2 months. While other forms of credit are less expensive, they are probably not always available. For example, the average interest rate is 6% per month from family/friends, and 4% per 1.5 months for ROSCAs, but the availability of both is likely limited. The interest rate on MFI/bank loans is also lower than digital credit (19% on average for 8 months), but these loans are certainly not instant.

3 Impacts of Digital Credit Access: Regression Discontinuity Analysis

In our first analysis, we use a regression discontinuity approach to estimate the reduced-form effects of digital credit access on a set of outcomes. In this section, we describe the administrative and survey data we use to estimate impacts, explain our sampling strategy and empirical specification, and present results.

3.1 Administrative data from Airtel and Credit Scoring Firm

We have 3 main sources of data from Airtel. First, we have Airtel's Know-Your-Customer (KYC) database, which includes first and last name, date of birth, gender, and the location of registration. Second, we have mobile money transaction data for the period just before credit scoring occurred (January-March 2019). Third, we have *Kutchova* loan data for every loan between July 2019 and May 2020. These data include the phone number of the borrower, date of the loan, the amount and status of the loan (i.e., open or closed) as of May 20, 2020, and fees incurred.

The credit scoring firm also provided us with information required to implement the regression discontinuity analysis. As discussed earlier, for each account, the credit scoring firm created a "predicted profitability" value (a continuous variable ranging from -.91 to -0.01), and used it to construct discrete scores ranging from 374 and 912. Those with a score of 834 or above (around 44,000, or $\sim$5% of those scored, corresponding to those with a predicted profitability of -0.14 and higher), were considered eligible and assigned to one of four "relaunch batches." However, due to budgetary constraints, only the first two batches (N1/N2) were granted access to the product.[17] The scoring firm provided us with the predicted profitability score, credit limits and a few other aggregated variables that were used for scoring. The firm did not reveal to us what variables went into the score. While some users qualified for a larger loan, the focus of the RDD

[17] The distributions of scores are very similar across batches (see Panel B of Figure A5), suggesting that the score itself was not used to determine batches. However, pre-scoring mobile money usage is different between the groups. N1/N2 users have lower peer-to-peer (P2P) transfers, lower cash-outs, lower cash-ins, and they received higher credit limits. In conversations with the scoring firm and Airtel, the decision to exclude N3/N4 users was driven by lack of funding, and, as evident in the data, it was decided that loans would be extended to subgroups with average lower credit limits. We therefore focus our analysis on the sample considered eligible only for the lowest credit limit (MWK 1,000).

analysis is around the smallest loan amount of MWK 1,000. The distribution of scores around the threshold eligibility score for MWK 1,000 is shown in Figure A8. Reassuringly, we see no bunching on either side of the threshold for either gender. We observe a smooth distribution of scores around the threshold of 834, indicating no evidence of manipulation.

3.2 Analysis Sample and Survey Data

Our analysis makes use of administrative and survey data. Within the administrative data, we construct an analysis sub-population of users around the threshold. We exclude existing users (groups E1 and E2) since they were scored using a different algorithm which also included their prior repayment history, and we do not have access to their scores. Among new users who scored below the threshold, we include everyone with a score of 827 and above. Among those above the threshold, we include everyone with a score of 842 and below and eligible only for the lowest credit limit (MWK 1,000), among those assigned to relaunch batches N1 and N2 (since N3 and N4, while scored as "eligible," did not ultimately receive access to the loans). The resulting sampling frame for our regression discontinuity design analysis consists of around 10,000 users.

To measure impacts, we conducted a phone survey with a random subset of users within the 827 to 842 score range across the eligibility threshold. Prior to sampling, we excluded a handful of "atypical" users (i.e., those with very rare types of transactions), those who were either under 18 (too young to provide informed consent) or over 80 years old (extremely rare). Since one of our stated objectives was to examine impacts separately for men and for women, we oversampled women, who make up only 41% of this subset of eligible borrowers and 36% of all eligible borrowers.[18] All our analyses include sampling weights.

The survey included time-invariant questions on demographics such as age and education, which we use to examine balance across the threshold. The survey also includes a number of questions on credit, including digital credit and all other sources of loans over the 3 months prior to the survey. For each loan source, we asked detailed questions about the last loan. This is the data previously discussed in section 2.4. To understand impacts on well-being, the survey

[18]For men, we sampled all users with scores from 831 to 839, 20% of users with a score of 820 and 25% of users with a score of 840. For women, we sampled all users with a score from 831 to 842 and sampled 50% of users with scores from 827 to 830.

included modules on financial security, savings and experience with unexpected shocks.

The survey took place over the phone between March 2 and April 8, 2020 (just as the COVID-19 crisis was taking hold).[19] We completed surveys with 2,896 users during those 5 weeks. In addition, 1,100 of those sampled for the RD survey had already been surveyed in October 2019 as part of the RCT described below. For those respondents, we did not administer a new survey in March 2020 and instead use the information collected in 2019. The October 2019 and March 2020 surveys were nearly identical, with minor exceptions.[20] Overall, almost 70% of those we attempted to survey were successfully surveyed (see Table A1 column 1). While this success rate is somewhat lower than for in-person surveys in Malawi,[21] it is high compared to typical success rates in phone-based surveys that cold-call people like we did (often no greater than 20%, as in Kasy and Sautmann (2021)), and in line with the 69% survey rate obtained by Suri et al. 2021 in Kenya.[22] Importantly, attrition was not differential above and below the threshold, as shown in Table A1.

3.3 Empirical specification, validation of RD design, and sample characteristics

Our main empirical specification is a robust non-parametric regression discontinuity approach, following Calonico et al. (2014). Specifically we estimate:

$$y_i = \beta_0 + \beta_1 s_i + \beta_2 Z_i + \beta_3 Z_i s_i + \gamma X_i + e_i \tag{1}$$

where s_i is the re-centered, continuous "predicted profit" variable that determined eligibility, Z_i is an indicator for being over the threshold, and X_i is a set of covariates. β_2 is the treatment effect of being eligible for loans.

We first evaluate the validity of our design by running this specification for a limited number of

[19] Malawi declared a "state of disaster" on March 20, 2020. This led to the immediate closure of schools and restrictions on transport and gatherings. A lockdown announced on April 14, 2020, was quickly declared unconstitutional by the Malawi Supreme Court and never implemented. See Aggarwal et al. (2021) for more detail on the effect of COVID-related disruptions in Malawi.

[20] The main shortcoming of the October 2019 survey for the RD analysis is that we only asked about the last *Kutchova* loan, not about all *Kutchova* borrowing over the past three months

[21] See for example Goldberg (2016), Giné et al. (2012), or Dupas et al. (2018).

[22] Surveyors attempted each number at least 5 times, at different times and days of the week in an effort to find people when they had time to talk.

covariates which are available in the Airtel KYC and adminstrative data. Results are presented in Table A1. These covariates include age and location (urban vs. rural) from the KYC database, and four measures of usage from the mobile money data (cash outs, cash ins, transfers sent, and transfers received). Of the 12 regressions in this table (6 covariates for two gender groups), only one is significant (age for women). While none of the mobile money measures are statistically significant, one caveat is that the standard errors are large.

Table A2 examines balance on characteristics measured in the survey. We look at one time-invariant characteristic (education), as well as other measures which are unlikely to be affected by access to a small loan, such as employment status, monthly income, household characteristics, marital status, home ownership, and access to electricity. The sample is much more affluent than the average Malawian. Among users just below the threshold, average years of education is 11.4 (11.8) for women (men), average reported monthly income is \$178 (\$227), and 73% (70%) have access to electricity. These are all far above average for the country of Malawi – for example, average years of education is reported at only 4.7 in the latest UN Human Development Report. The table also shows no evidence of imbalance across the threshold: only 1 of 16 coefficients is significant (monthly income for men). In the analysis below, we control for the covariates shown in Table A2 for the survey-based outcomes, as well as for the following administrative data variables for both administrative and survey-based outcomes: gender, age, an indicator for whether a user was registered in urban/rural location, whether the user has multiple SIM cards, and whether the user was automatically approved for an Airtel Money account at the time they registered their SIM card.

3.4 Regression Discontinuity Results

Credit

Table 3 examines the impact of credit eligibility on take-up of the digital loan itself, using only administrative data from Airtel. The first 3 columns show the extensive margin, while the last 3 show the value of loans. For each measure, we present results for the entire sample of users within the range considered for the RD (827-842, around the cutoff of 834), and for the sample that was successfully surveyed. We show results for the entire period after the relaunch (which occurred in July 2019), as well as for the 3 months prior to the survey (since this is the look-back period in the survey). We show pooled results in the main tables, and present results separately for women and for men in Appendix B. All estimated effects are highly significant, with p-values $\leq$0.001.

Crossing the eligibility threshold causes a 34 percentage points increase in borrowing from *Kutchova* for the universe of accounts, and similarly a 38 percentage points increase for our survey sample (these are both on a base of almost zero – we observe minimal access among those below the threshold). Over the 3 months prior to the survey, the effect is smaller (13 percentage points). The total amount borrowed increases by $1.8 for the average eligible user, and $2.2 for the average respondent in our survey sample. The effects are observed for both gender, and somewhat more pronounced among females (Table B1).

While the administrative data is useful for showing take-up of digital credit itself, the survey data is necessary to measure effects on other sources of credit. These results are shown in Table 4, and show loans over the 3 months prior to the survey.[23] Column 1 shows the extensive margin for *Kutchova*, and shows a 12 percentage point increase (very similar to that in the administrative data). Column 2 shows effects on take-up of any loan, which is slightly larger (though insignificantly so) than the first stage for digital credit itself, which suggests that digital loans were new loans that did not crowd out existing credit (albeit for small sums). We explore this further in Columns 3-5, which show the number of loans from various other sources (digital airtime, friends/family, and VSLAs/ROSCAs). Each coefficient is insignificant except for digital airtime loans, though confidence intervals include some fairly large values. Column 6 shows the total value of credit across all sources, in dollars. The effect is positive but insignificant. The confidence intervals are wide however, and in any case the value of digital loans is small relative to total credit (which is about $30).

Downstream Outcomes

Table 5 shows effects on relevant downstream outcomes. The first 4 columns measure self-reported financial security. The dependent variable in Column 1 is a dummy for a yes/no question on whether the respondent is satisfied with her financial well-being. We find a statistically significant increase of 12 percentage points (on a base of 55%). The dependent variable

[23]This analysis includes only a subset of the survey sample, those administered the survey in March, since the October survey did not ask about all loans over the past three months but only about the last loan.

in Column 2 is a question about a respondent's degree of preparation for future emergencies (which ranges from 1-4), which we standardize for this analysis. We see no effect on this outcome, which may not be surprising since a MWK 1,000 loan (just over $1) clearly does not suffice to cope with most emergencies. In our data, most shocks people report are for far too much money to be dealt with with a few dollars – of those that required money to deal with, we asked respondents how much they needed to fully cope with the shock, and the median (average) amount was $26 ($208) (with a standard deviation of $1,104). The dependent variable in Column 3 is an index of ability to pay for non-food expenses.[24] We find a positive but insignificant effect on this index. Column 4 is a food security index, which is a standardized index of a set of 4 questions that are similar to those used in the household food insecurity score.[25] We find small and statistically insignificant effects for both. In Column 5, the dependent variable is an indicator equal to 1 if the respondent used digital credit as a source of cash to cope with shocks. Consistent with Column 2, we find that virtually nobody does this. This is in contrast with the finding in Suri et al. (2021), likely due to the fact that the value of credit people take out here is much lower: our first stage is only $2, compared to roughly $10 in Suri et al. (2021). Finally, in Column 6, we look at total savings as reported by the respondent. The coefficient on total savings is positive and fairly large ($5, about 4.1% of the baseline mean), though not significant (p-value = 0.7). In Column 7, we look at liquid savings and the coefficient is negative and fairly large (-$11, about 14% of the non-eligible mean), but, again, the coefficient is not significant (p-value= 0.3). Because $5, let alone $11, are considerably greater than the amount borrowed from *Kutchova*, and because they go in opposite directions, it is difficult to imagine that either of these insignificant coefficients reflects anything causal; instead, we suspect the savings data is noisy.

To summarize this table, we do not see strong evidence of big effects either way – neither clearly harmful as feared by some observers, nor clearly helpful. The breakdown by gender shown in Table B3 suggests that positive effects on financial security may be stronger for women, and the potential negative effects on liquid savings may be driven by men.

[24] This index is created from questions which ask about a number of expense categories (school, health expenditures, bills, and helping family/friends in times of need). For each category, the question is: "In the past 3 months, have you found it difficult to pay for [the given expense]?"

[25] Specifically, these questions ask for the number of times, over the past 90 days, that a respondent (1) relied on less expensive foods, (2) limited portion size at meal times, (3) reduced the number of meals eaten in a day, and (4) borrowed food or relied on help from a friend or relative to eat.

3.5 Summary of regression discontinuity results

Our RD analysis confirms that there is robust demand for digital loans, and consequently a first-stage exists. However, because loan sizes are small, the value of loans is modest. Consequently, it may be no surprise that effects on downstream outcomes are limited – we do document some suggestive evidence of a small positive effect on financial well-being, but see little evidence of effects on most outcomes. All in all, our results suggest a possible modest benefit of the loans, and we do not observe much cause for concern.

To provide further descriptive evidence on borrower's experience with digital credit, we asked some debriefing questions of *Kutchova* borrowers at the end of the phone survey, which we present in Table 6. In Panel A, we asked people about why they used digital credit the last time they took out a loan. About 24% report that they had the money available but found *Kutchova* more accessible; of the remaining 76%, 28% reported that they would have the money coming soon but did not have it on hand at the time, while another 48% reported not having the funds in the immediate future. Panel B asks similar questions in another way, focusing on loans that were rejected by the system (which happens when the system lacks liquidity). Twenty percent of borrowers reported that this happened to them. When it did, about half of people (48%) either do not fully incur the expense, or do not incur it at all. The remaining borrowers are split between borrowing elsewhere (26%) or using savings (15%). Both Panels B and C therefore suggest that, even though loan amounts are small, digital credit still fills a need for borrowers.

Panel C shows information on self-reported satisfaction with digital loans. We find that while regretting a loan is not unheard of, it is rare: only 12% reported regretting a past loan. Similarly, 90% report liking *Kutchova*, with many reporting that the main reason is that they got the money immediately, on their phone. Interestingly, about 14% report that they like *Kutchova* specifically because the interest rate is actually lower than alternatives.

Overall then, while we certainly do not see transformative effects (nor is it reasonable to see them with loan sizes this small), the evidence suggests that digital credit fills a small hole, and does not dig one (at least on average).

4 Financial Literary RCT

While the results presented so far do not ring alarm bells, one reason for possible concern is that many borrowers pay loans back late, incurring substantial fees. For example, in Table 1, we see that only 38% of new borrowers pay back fully on time, while another 47% pay back fully, but late (ultimately paying an average interest rate of about 27% due to late fees, rather than the 10% rate if paid back on time). These results are similar to research in the US showing that people pay too little attention to overdraft fees or late payment fees on credit cards. In our case, people who are paying fully but late are effectively subsidizing those who default, because the fees they pay keep the product profitable.

One reason that so many people pay back late might be that they simply do not know that there are late fees. Table 6 Panel D shows some basic statistics on knowledge. It is clear that most borrowers do not know basic terms. Only 29% know the exact fee, only about half know when the loan is due, less than half know that there is a late fee, and over a third report that they do not know what would happen if they do not pay back on time. These figures are consistent with other research which has shown limited knowledge among consumers of digital credit products in other countries in Africa.

At the start of the project, we conjectured that lack of knowledge about the risks of digital borrowing could be a driver of digital credit demand, and that informing people might reduce demand. To investigate this, we conducted an RCT with eligible borrowers, which we discuss in this section.

4.1 Experimental Design and Randomization

The timeline of the RCT is shown in Figure A9. As discussed above, Kutchova relaunched on July 1, 2019. Starting on July 31, 2019, we implemented a financial literacy RCT with the 26,467 newly eligible customers (24,139 of which have non-missing gender in the KYC data). These users were randomized into four treatment conditions, stratified by several characteristics.[26]

[26] Stratification variables were: the relaunch batch to which the user was assigned (N1, N2, E1, or E2); a set of variables in the Airtel administrative data: whether the respondent was automatically enrolled in mobile money upon SIM card registration, quantiles for the year of birth in the KYC data, whether the respondent was eligible for loans higher than MWK 1,000 (as opposed to loans of MWK 1,000 or less), gender, whether the respondent lived in an urban area, and whether the respondent had more than one SIM card (defined as two registered SIM cards sharing the same first name, last name, date of birth, and gender). This created 495

The main treatment group of interest is the financial literacy ("Finlit") group. Users in this group received a phone call using interactive voice response (IVR) software, which walked participants through a 15-minute example scenario which was developed by the research team, based on the Terms and Conditions provided by Airtel at the time of the July 2019 relaunch. The entire script is included as Appendix C. The scenario involved a shopkeeper who was purchasing inventory for her shop, and was deciding between using a digital loan or other sources.[27] The Finlit module stated the 10% fee for taking out the loan, highlighted the fact that the customer will be charged a hefty cash-out fee when they withdraw the loan from their account, and informed customers of the existence of late fees. The module mentioned the late fee schedule as stipulated in Airtel's Terms and Conditions (2.5% for every 15 days due, up to a maximum of 3 times), and also warned borrowers that policies regarding late fees (and other fees) can be changed at any time so potential borrowers should check terms before taking out loans. In practice (and in violation of the posted Terms and Conditions), the lender charged a much higher late fee of 12.5%. As mentioned earlier, there was no way borrowers could learn about the true late fee being 12.5% before taking a loan, and even upon borrowing, they would not be informed of the 12.5% until 24 hours prior to the due date, when they would receive an SMS reminder stating: "Your outstanding balance [MWK AMOUNT] is payable [DATE, TIME]. Failure to settle will attract a penalty of 12.5%."[28]

Precisely because of the lack of transparency around late fees and high potential costs, the Finlit module discussed and concluded with other options for financing the purchase, including asking relatives for credit or using personal savings. The module also noted the possibility that overdue loans would be reported to the credit bureau—something that borrowers are warned about by Airtel via SMS once they are late on repayment, though in practice Airtel has told us that they have not been reporting anyone.

Respondents were incentivized to initiate the module via a MWK 500 incentive payment,

strata with 53 users on average (range 4 to 614). Focusing on customers with non-missing gender information in the KYC database, there are 442 strata with 54 users on average.

[27]The scenario focused on the cost of credit and so used an example where digital credit could be used for larger loans like those required to purchase inventory.

[28]The research team was never informed directly by Airtel about the *de facto* terms, and discovered the 12.5% penalty upon receiving the Kutchova loan dataset from Airtel and analyzing it at the end of our study period. We have since then filed an incident report with the IRB and organized for IPA to send SMSes to all those in the Finlit and SMS-only groups to inform them of the current late fee schedule and warn them that Airtel can change late fees without informing customers.

paid out in airtime, conditional on having gone through the module.[29] Respondents could initiate the module in two ways. The most common way was via an automated robocall. When users picked up the call, they were informed that if they stayed on the line, they would be automatically connected to the module, and would be eligible to receive the incentive payment. Because the probability of picking up was low, users were called repeatedly (up to 5 times, conditional on not having initiated the module before) to conduct the module. The second method was for users to call into the line directly. Respondents received a text message with the call-in number, which informed them of the incentive payment.

In addition to the IVR module, the Finlit group also received 2 text messages repeating the digital loan terms and conditions. These messages had two purposes: to remind people who had participated in the Finlit module of what they had learned, and to provide information in a light-touch manner to those who didn't choose to go through the module.

The second treatment group is the "salience" group. This group was constructed to serve as a comparison for the selection induced by having to stay on the line for the IVR module, and to equalize the incentive payment. This group was contacted in the exact same way as the Finlit group, and was incentivized the same way during the introduction message (MWK 500 airtime reward upon completion). The only difference in their experience was that the IVR module they participated in was much shorter (only 3 minutes) and did not deliver any specific message about digital borrowing; it only informed them of the existence of *Kutchova*. The third group (the "Info SMS" group) received the same two text messages as the Finlit group, without the IVR quiz. The fourth group was a pure control group.

The IVR and text message campaigns took place between July 31 and August 15, 2019, and reached up to 1,000 individuals per day. Figure A10 shows take-up of each of the treatments. Panel A uses administrative data from the IVR database, and shows high take-up of the modules. Among women, 47.4% took the Finlit module, and 49.9% took the salience module; for men, takeup was even higher (50.4% and 55.9%). These rates are much higher than in other IVR studies of which we are aware. The fact that takeup is nearly identical between Finlit and Salience means that the same share of respondents received the incentive payment in the two groups, equalizing the income effect. Panel B replicates this analysis using survey recall questions of interacting with the module. The pattern is very similar, though effect sizes are

[29]In practice, we paid out incentives to anyone who finished the first 10 of the 13 sections in the module.

attenuated, perhaps because some people forgot. Even in the surveys, however, about 47-50% of women and 41-44% of men report interacting with the module.

4.2 Data, Summary Statistics, and Experimental Balance

We have two sources of data to analyze impacts. First, we received administrative data from Airtel covering Kutchova loans taken between July 1, 2019 and May 20, 2020. For each loan, we know whether and when it was repaid, and fees applied.

Second, we implemented surveys with a random subset of *Kutchova* eligible users to measure whether the intervention changed knowledge, attitudes and practices, and to quantify how people use loans and what other sources of credit they use. We started surveys at the end of September 2019. We initially sampled around 8,256 respondents for surveys, but Airtel requested that we stopped surveying after one month.[30] Altogether, we attempted to reach 4,445 respondents, of which 3,321 had completed a survey. The survey rate of 75% among attempted customers is, here again, relatively high for a cold-call phone survey.

We show balance (separately by gender) on the administrative (Table A3) and survey (Table A4) variables used to check balance in the RD analysis. We find no evidence that our randomization failed to generate comparable groups.

4.3 RCT Results

We examine the effect of the financial literacy intervention on the primary and secondary outcomes pre-registered in the AEA RCT Registry: *Kutchova* borrowing and repayment using administrative data, and knowledge of loan terms from the survey. We did not pre-specify any downstream outcomes because we expected the first stage on loan demand to be modest (which is what we find). However, we do examine several non pre-specified indicators of satisfaction with digital credit and regret in order to provide some descriptive evidence on the consumer experience. For each outcome, we estimate the following regression:

[30] Airtel required us to register with the Malawi Communication Regulatory Authority (MACRA) for a "short code" account. When a user gets a phone call from such a short code, the caller ID will show only 3 digits (as opposed to a normal 8 digit phone number), and users can be confident that these calls are from legitimate registered accounts. Our request was only approved in March 2020, so we were unable to survey between October and March.

$$y_i = \beta + \theta Finlit_i + \alpha SALIENCE_i + \delta SMS_i + \phi X_i + \epsilon_i \tag{2}$$

where y is the outcome for individual i, and $Finlit$, $SALIENCE$, and SMS are treatment indicators. X_i is a set of covariates including the stratification variables.[31]

Knowledge

Table 7 shows effects on awareness of *Kutchova's* key features, indicating that the Finlit treatment improved knowledge of costs and risks.[32] The treatment group is 17.9 percentage points more likely to know that the initial fee on the loan is 10%, 16 percentage points more likely to know that the loan is due within 15 days, 15 percentage points more likely to know that there is a late fee, and 15 percentage points less likely to report that they do not know what happens if they don't pay back. The results are similar across gender, as shown in Table B4.

An interesting note is that, during our follow-up surveys, respondents were asked a few descriptive questions about *Kutchova*. While the research team's prior was that the IVR module would make people think that *Kutchova* was relatively expensive, 67% of Finlit respondents reported that the module made them think *Kutchova* was *less* expensive than they previously thought (and only 9% updated the other way). Similarly, 62% reported that they were more likely to use *Kutchova* after taking the module, and only 20% less. We interpret this result as suggestive that people do not have much information on what the costs of *Kutchova* are, and do not find the rate exorbitant when it is disclosed. An alternative is that people expected the late fee to be 12.5%, and were wrongly induced to think the terms were better since the Finlit module, based on the official Terms and Conditions, reported the late fee was 2.5%. While this is a possibility, we do not think it is likely, given that the vast majority of people report not even knowing that there exists a late fee. What's more, we see no difference in these responses based on whether respondents had taken a *Kutchova* loan prior to the Finlit intervention.

[31] Results with strata fixed effects are summarized in appendix Table B4. We prefer to control for stratification variables than to include strata fixed effects in the main tables, because we reached only 55% of the original sample, hence many strata end up with zero users in the Control group or zero users in the Finlit group, so the effective sample size with strata fixed effects is quite reduced, and precision too.

[32] Note that the averages for the control group in this table indicate lower awareness than what was shown in Table 6. This is not surprising since the RCT survey was done 3 months after the launch of *Kutchova*, while the RD survey was done 9 months later, and awareness increased somewhat in the meantime.

Loan demand

Table 8 shows the impacts on loan demand over 3 time periods: before the treatment began (Columns 1-3), which is included to show pre-treatment balance; 0-3 months post-treatment (Columns 4-6), which is included to look at "short-term" effects; and 3-9 months post-treatment (Columns 7-9), for "longer-term" effects.

Unfortunately, there is some evidence of imbalance: in the pre-treatment period (essentially July 2019, the first month of the re-launch), the Finlit group was more likely to have taken out a loan (by 1.9 percentage points, on a base of 22.6%) and to have taken out more loans (about a 10% increase relative to the control group). Total pre-treatment amount borrowed is 6.2% higher for the Finlit group (p-value=0.087). For this reason, we control for pre-treatment borrowing behavior in the remaining columns.

In Columns 4-6, we see evidence of an *increase* in loan demand 0-3 months post-treatment. Respondents in the Finlit group are 4.0 percentage points more likely to take a loan (on a base of 25.3%) and take out about 0.13 more loans (a 22% increase on a base of 0.62). The total amount borrowed from *Kutchova* 0-3 months post-treatment is 18% larger (+0.366 from a base of 2.05) in the Finlit group (three times the size of the gap pre-treatment). This increase is attenuated but still evident in the 3-9 months after treatment: respondents are still 1.8 percentage points more likely to take out a loan over that window, and the total amount borrowed is 9% higher (p-value=0.060).

Interestingly, we see a positive but small effect (0.013, or about 1/3 the size of the Finlit effect) on take-up for the salience treatment in the short run. Though this effect isn't quite significant at 5%, the p-value is 0.086. We can reject that this effect is equal to that of Finlit, but this does suggest that part of the Finlit effect might be driven by a marketing or salience channel. This effect fades out over time, however, and it seems clear that Finlit has an effect over and above salience.

Loan Repayment

We show effects on loan repayment in several different ways. First, we exploit the randomization of the date at which individuals sampled for one of the treatments were treated, which we present in Figure 4. Using an event-study analysis, we find that those who received the Finlit information a few days before the due date are no more likely to have repaid on time, and did not end up paying lower fees, than those who received the information right after. The Info SMS treatment also made no difference, nor did the Salience treatment. We take this as evidence that Finlit had no effect on repayment behavior for borrowers who had already taken out loans. We interpret this (lack of an) effect as evidence that information alone was not sufficient to alter repayment behavior among infra-marginal users, i.e., those who chose to borrow under incomplete information.

However, we know that Finlit (and salience, to a lesser extent) changed the composition of borrowers, by inducing more people to take out loans. Table 9 show effects on repayment of new loans over the 9 months following the RCT intervention period. The unit of observation is a loan, and we look at 5 measures of loan performance: the percentage of the loan that is repaid (i.e., all repayments and fees divided by the initial loan size), whether the loan was fully paid back on time, whether the loan was fully paid back late (i.e., incurring late fees), whether the loan was only partially paid back, and whether none of the loan was repaid.

We find that financial literacy improved all of these loan outcomes. From Column 1, the bank return is 0.9% higher (on a base return of about 5.7%) when lending to individuals in the Finlit treatment. This is not due to higher late fees: from Column 2, Finlit borrowers are more likely to pay back on time. Instead, it is because Finlit borrowers are less likely to fully default (Column 5); Finlit borrowers are also somewhat less likely to pay back late. Overall, these results suggest that Finlit (modestly) improved outcomes for the lender.

While the loan level effects show some improvement in repayment, borrowers typically take out multiple loans and so the value of late fees, and the probability of default, may accumulate over time for a given borrower. In Table 10, we present results at the user level. Columns 1-4 show effects for pre-existing users (who already had access before the relaunch, groups E1 and E2) and Columns 5-8 show effects for new users (who only became eligible during the relaunch). We show the total amount borrowed, the total late fees paid (both as a cumulative percent of the total amount borrowed and in levels), and whether the borrower ever defaulted.

Results for pre-existing users show no significant effect on usage, fees, or default. Pre-existing users use *Kutchova* much more than new users (average amount borrowed is over \$22 vs. \$3) and presumably are already positively selected (they did not default earlier) and better aware of terms. But effects are large for new users. New users who participated in Finlit borrow significantly more (which indicates that new users were driving the earlier results). They are no more likely to pay late fees expressed as a percentage of amount borrowed (Column 6), but since they borrow more the total amount of late fees paid are higher. What's more, they are 1.7 percentage points more likely to be in default after 9 months (on a base of 14.9%). In other words, since they take out more loans, even if their odds of default is slightly smaller on each loan, their cumulative likelihood of default increases. Thus, if default is costly to the borrower, there is cause for concern: as long as there is some non-zero risk of default on any given loan due to e.g. unexpected shocks, any intervention that increases demand for loans, even if it is designed to protect customers, is at risk of ultimately increasing the share of customers on the "defaulters" list.

Regret and Attitudes to *Kutchova*

In Table A5, we show effects on whether respondents regretted taking out a loan, whether they liked the product, reasons for disliking the product, and whether they would use *Kutchova* to cope with an emergency. Despite taking out more loans and thereby increasing their probability of being in default, Finlit respondents are not more likely to regret a loan (Column 1, the coefficient is in fact negative, p-value=0.184), and not less likely to report liking the product (Column 2, the coefficient is in fact positive, p-value=0.219). Surprisingly, we find statistically significant effects on both outcomes for the SMS treatment, despite no evidence of prior effects of those treatments. From Column 3, we see from the control mean that about 9.3% of control respondents report disliking *Kutchova* because it is tempting to take out an unnecessary loan, and this is not significantly different in the Finlit group. Consistent with prior results, we find in Column 4 that respondents in Finlit are no more likely to report that they dislike *Kutchova* because it is more expensive than other options.

Finally, the control means in Columns 5 and 6 show that, consistent with the findings in the RD analysis, only a very small share of borrowers consider *Kutchova* useful to cope with urgent cash needs. But consistent with the effect on borrowing, the Finlit treatment increased the likelihood that respondents mention *Kutchova* as a coping mechanism for small shocks.

5 Heterogeneity

The effects of digital credit are almost certainly heterogeneous, with some borrowers benefiting from an easy source of cash while others may take out loans they don't need and may struggle to pay them off. One obvious sign of heterogeneity is simply that some borrowers pay back loans on time and avoid late fees, while many others do not. The lender has an incentive to lend to those inattentive borrowers who continually pay back late, and thus there is clearly potential for harm. While we leave an exhaustive analysis of this type of heterogeneity for future work, this section provides some evidence on the characteristics of those most vulnerable to such harm.

Figure 5 shows distributions for total loans taken and total loans repaid late. About half (46.5%) of borrowers repaid late fees twice or more (top panel, hollow bars). And 16% repaid the maximum late penalty (22.5%) twice or more (bottom panel, hollow bars). Recall that the *total* fee paid for such borrowers is 32.5% of the value of the loan, since there is the 10% facilitation fee (and a whopping 40% if they cashed out the loan, given the 8% cashout fee). Why do borrowers engage in repeat borrowing at such exorbitant rates? And who are those who do so?

Figure 6 shows how total late fees paid vary with the credit score. Recall that the credit score assigned by the third party was an increasing step function of the "predicted profitability" score. Conditional on being a borrower (Panel A), total late fees paid are actually *increasing* with the credit score (i.e., those with higher credit scores pay back late more often). Among the entire pool of eligible customers (Panel B), the credit score predicts late fees somewhat for women, but not for men, suggesting that men with higher credit scores are less likely to demand loans.

Table 11 looks at the characteristics of those who end up paying late fees (among those eligible for MKW 1,000 loans). We consider outcomes such as total late fees paid, whether someone paid late fees more than once, whether they ever paid the maximum late fee, and whether they ever repaid the loan on the due date but *after* the due time (i.e., they failed to transfer money from their mobile money account on time, so Airtel did it on their behalf as "auto-recovery" after charging the hefty penalty fee).

Panel A looks at characteristics available for the full sample in the administrative data. Some clear patterns emerge. Namely, elderly users borrow less often and as a result are much less likely to pay late fees. In contrast, younger users, and those with more active mobile money usage, are much more likely to pay high fees and to do so repeatedly. They are more likely to make the mistake of not paying on time even though they have the cash available in their mobile money account. They were also more likely to borrow on July 23 or 24, 2019 – two dates on which we observe a surge in borrowing in response to an advertisement campaign by Airtel. Just under 10% of those eligible responded to the ad campaign, and as shown in Figure A11, they were significantly less likely to repay their loan, suggesting that the marginal loan induced by the marketing campaign may have been a loan that should not have been taken.

Panel B of Table 11 exploits the survey data to look at other correlates of aberrant borrowing behavior. Note that we include (but do not show) the administrative variables shown in Panel A as controls in the regressions used to generate the coefficients shown in Panel B, and we also control for the Finlit RCT assignment. We only have a limited set of characteristics to examine, but here again we observe some clear pattern. In particular, among those eligible for loans of MKW 1,000, the more educated borrow significantly more and pay significantly more fees.

To summarize these results, it seems that those most likely to make borrowing mistakes (to end up paying high late fees or to borrow in response to marketing rather than a true underlying need) are *not* the poorest. They seem to be individuals with a higher standard of living to start with. The fees may represent only a small sum for them, even if high in percentage terms, since the loan amounts are fairly low to start with. It remains a puzzle as to why they use the loan in the first place. Over the phone, it was not possible to measure traits such as time preferences, attentiveness or impulsiveness. As a result, we cannot test whether borrowers who are more present-biased, less attentive or who lack self-control end up paying higher fees. We leave this for future work.

6 Conclusion

Widespread access to digital credit represents a revolutionary change in financial access. Digital credit offers unprecedented reductions in transaction costs and waiting times; in many countries, digital credit is already far outpacing traditional lending. But the same characteristics of digital credit that can revolutionize financial access also have the potential to harm customers, especially in environments in which people may be in need of cash but consumer protection laws are limited or not strictly enforced. In our study, many customers take out loans without knowing details of the terms, and many end up paying late, incurring large fees. The lender takes advantage of this ignorance, charging late fees well above those disclosed in the terms and conditions; consequently, some borrowers are paying rates as high as 32.5%, over just 6 weeks (equivalent to an APR of 1,000%).

In the first part of our study, we examine the effect of access to credit using a regression discontinuity design, and find modestly positive, though mostly statistically insignificant effects on various measures of financial well-being. These results are very much in line with other recent evidence from Kenya (Suri et al. 2021) and Nigeria (Björkegren et al. 2021) and suggest that products, as currently offered, are not that impactful (which may not be surprising since loan sizes are small, especially in our study in which the average loan ended up being only about $1). Regulators should be wary, however, since digital credit is only beginning to take off in many countries, and loan sizes and risks have the potential to rapidly proliferate.

In the second part of our study, we evaluate one potential consumer protection initiative: an IVR financial literacy training to lay out the sizeable fees to borrowers, discuss the risks of default (including reporting to the credit bureau), and suggest using savings instead. Contrary to our expectations and to prior studies such as Bertrand and Morse (2011), we find that this intervention actually *increased* demand for loans, speaking to the huge demand for credit in Malawi. The intervention also marginally increased repayment, showing positive effects of financial literacy for the lender. However, by increasing loan demand, the intervention also increased the proportion of borrowers who defaulted on at least one loan (since borrowers took out more loans).

Our results therefore clearly demonstrate both the demand for digital loans, even at seemingly exorbitant interest rates, and the need for consumer protection laws such as mandatory disclosure. Intense demand for credit, hidden fees, and low consumer awareness provide the ingredients for predatory lending. This is especially worrying given that, by their very nature, short-term, high-cost loans like *Kutchova* have limited upside potential. In particular, these loans cannot be used for longer-term investments in productive activities. While the concept of digital credit as an idea is promising, the reality of the products being offered is underwhelming.

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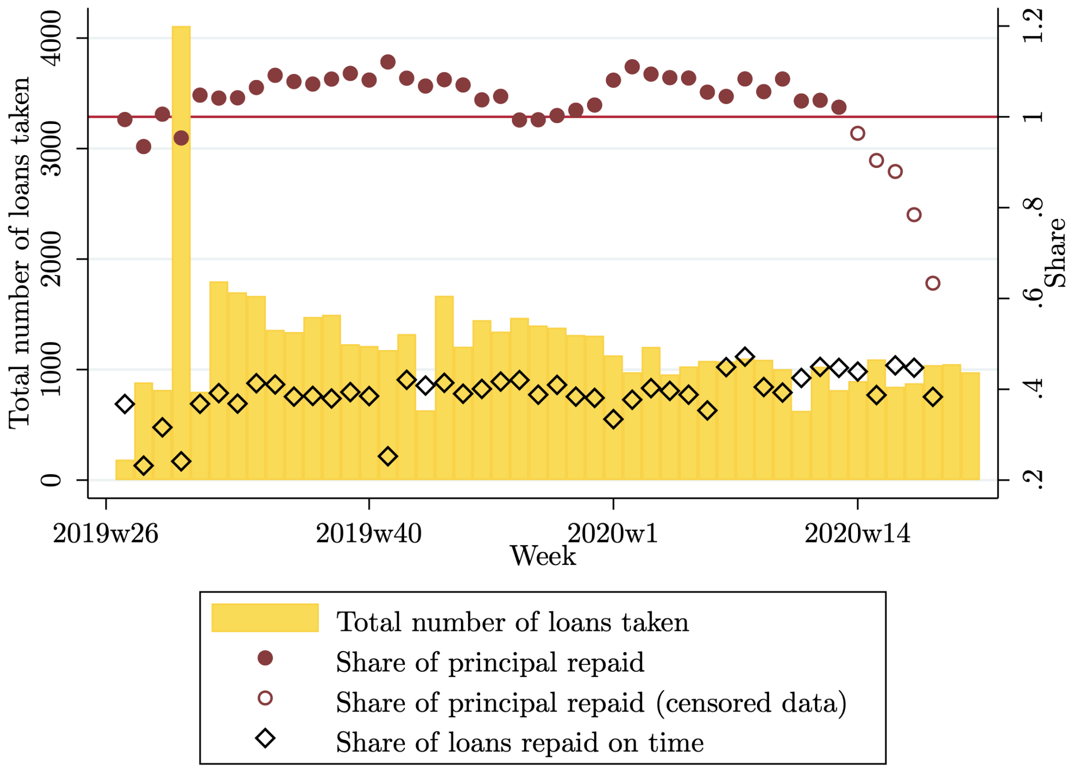
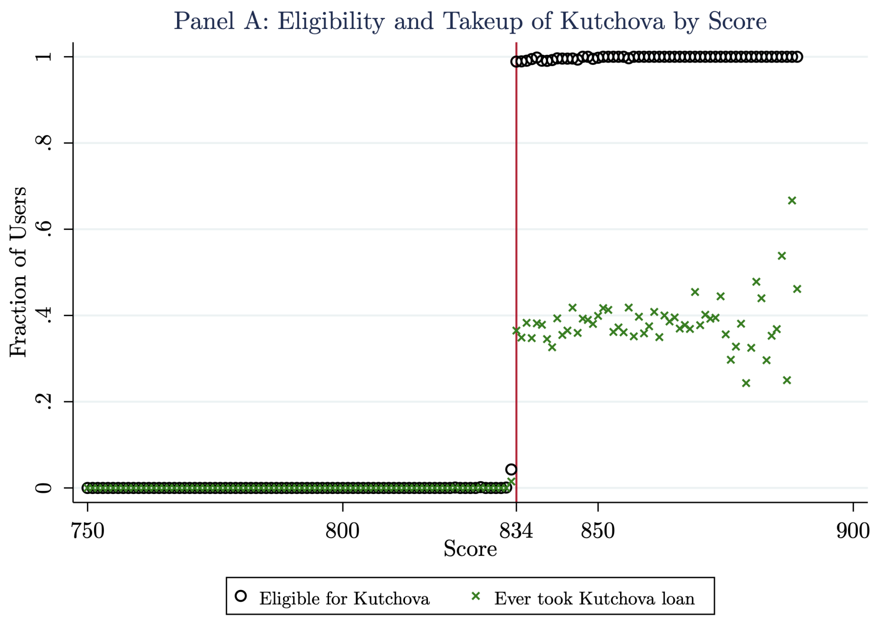
Figure 1: Take Up and Repayment of Kutchova Loans Over Time



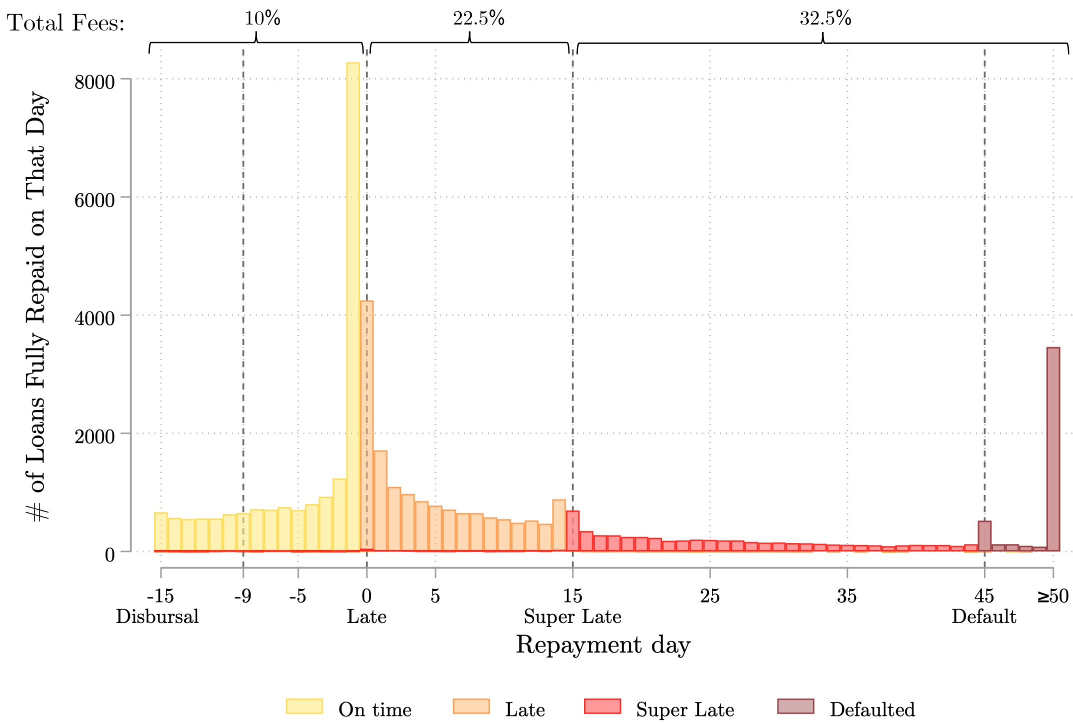
Notes: Source: Administrative Data on Kutchoval loans obtained from Airtel. Information on loan repayment for loans taken in the 8 weeks preceding May 20, 2020 (when the data was shared with the research team) is truncated (censored) since some borrowers take up to 8 weeks to repay in full. This explains the lower repayment figures in the later period (hollow dots).

Figure 2: Eligibility and Take-up of Kutchova



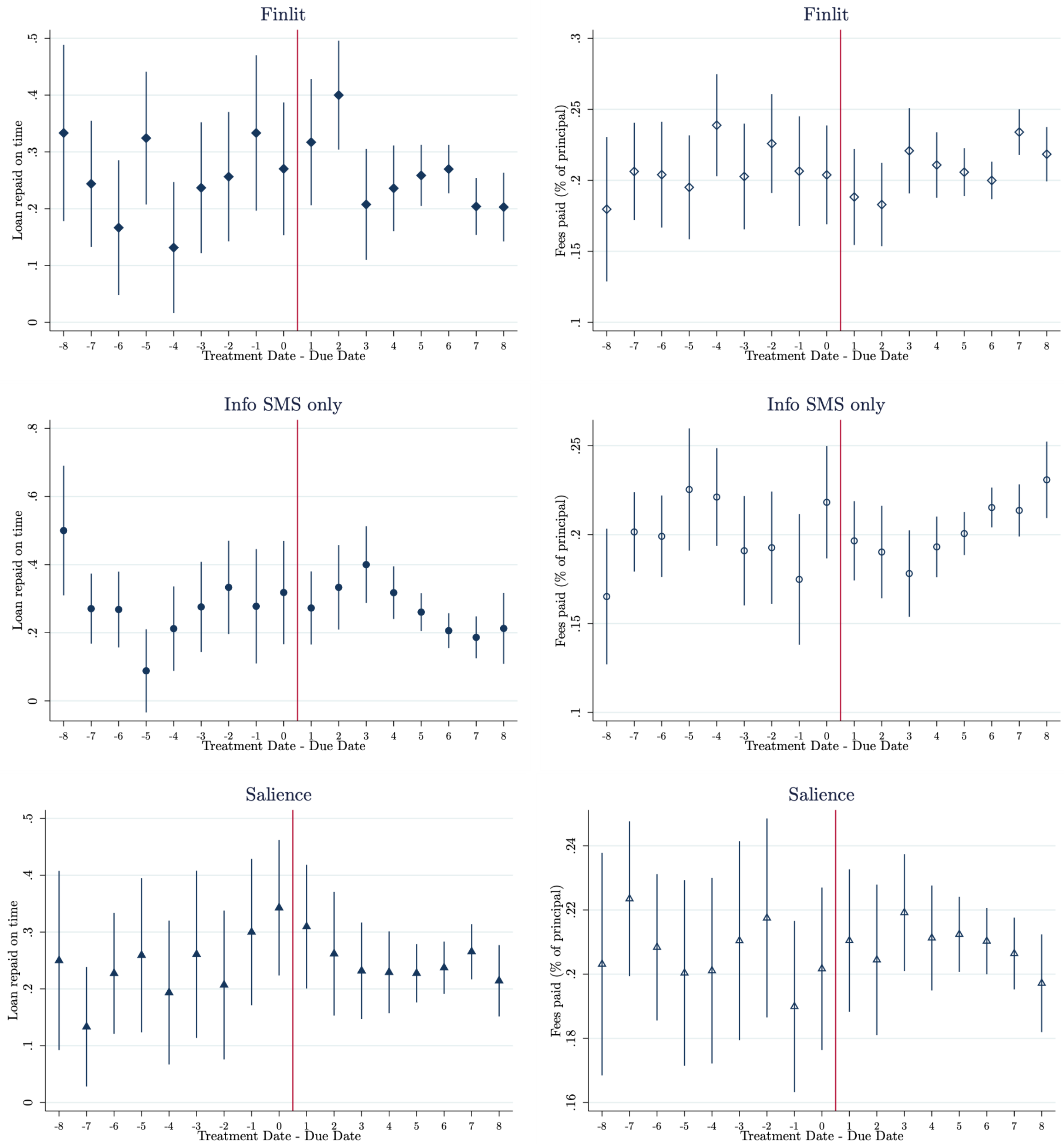
Notes: Data Source: Administrative data. Sample exclude customers with a credit limit above MWK 1,000. Existing Kutchova users (E1 and E2) and those with a score above the threshold but not included in the relaunch (N3 and N4) excluded. We do not have a score for E1 and E2, and take-up for N3 and N4 is zero by construction.

Figure 3: Repayment of Kutchova Loans



Notes: Source: Administrative Data on Kutchoval loans obtained from Airtel. Unit of observation: Loan. Loans with incomplete reimbursement information (missing disbursal or repayment date) and loans taken in the 8 weeks preceding May 20, 2020 (when the data was shared with the research team) are dropped since some borrowers take up to 8 weeks to repay in full. The final sample is composed of almost 44,000 loans. Loans are disbursed on day -15 in the figure. Loans are due within 7 days of disbursal, with a grace period of 8 additional days. After the due date (day 0, 15 days after the loan's disbursal), a loan is considered "late". A 12.5% late fee (2.5% penalty fee + 10% facilitation fee) is applied to late loans, in addition to the original 10% facilitation fee. If the loan is still outstanding after 15 additional days (day 15), the 10% facilitation fee is re-applied. After 45 late days (day 45), a loan is declared defaulted, no further fees are charged and Airtel attempts to recover the outstanding amount automatically using funds from the user's Kutchova Save account. The maximum late fee amount is 32.5%. Customers receive a text from Airtel within 24 hours before the due date informing them of the outstanding amount, due date, and late fees (see Figure A3). See Figure A1 for details on Airtel's Terms and Conditions. According to Kutchova's FAQ 8 (link: `https://airtel.mw/kutchova-T-and-C`), Airtel can start attempting autorecovery 7 days after the loan's disbursal (day -9 in the graph), but our data suggests they do not attempt auto-recovery until *after* the due time is past.

Figure 4: RCT Event Study: Impact on Outstanding Loans

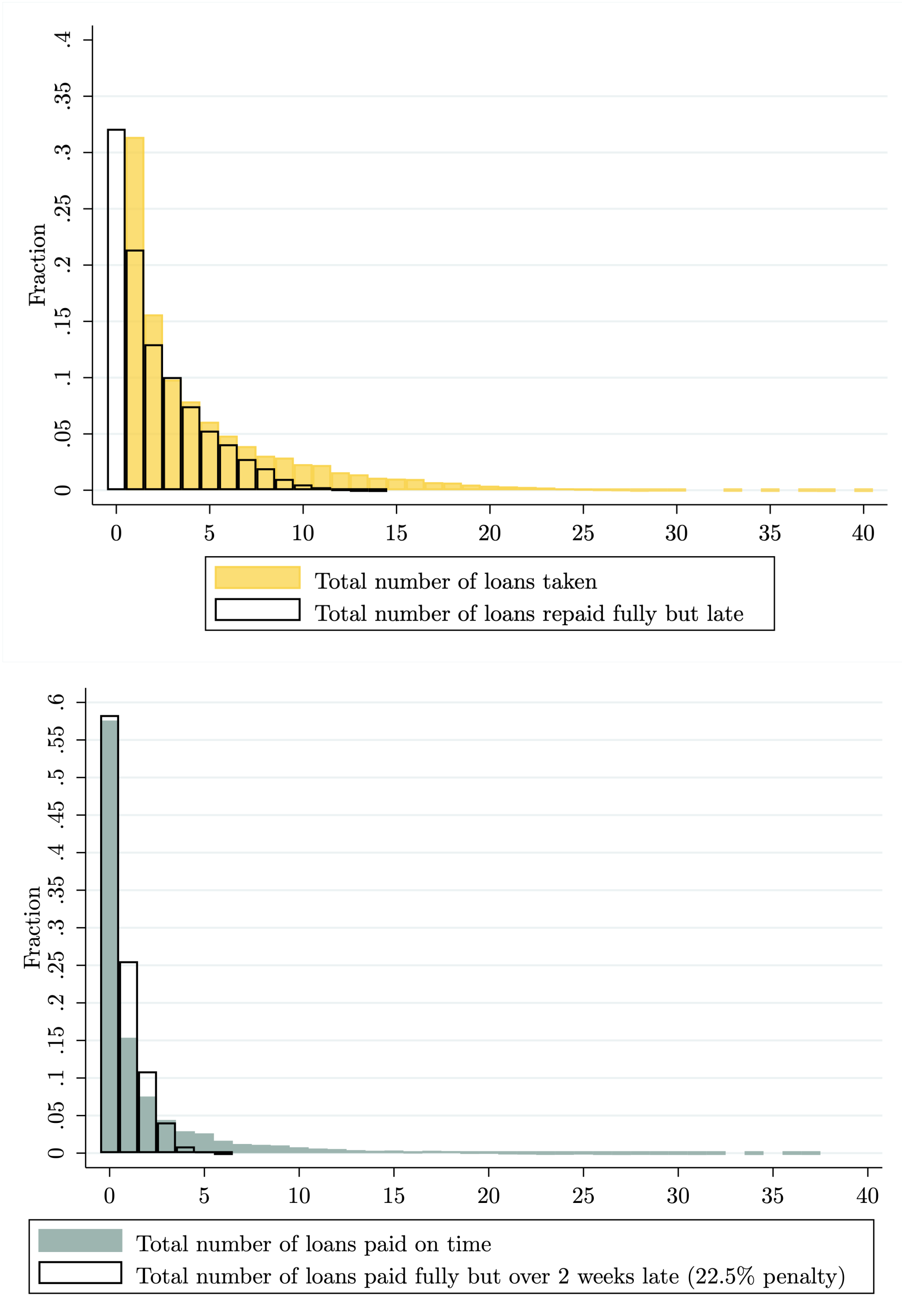


(a) On-Time Repayment

(b) Fees Paid

Notes: Source: Administrative Data. Unit of observation: Loan. Sample includes 3,144 loans taken by individuals sampled for either Finlit, InfoSMS or Salience, *before* the launch of the RCT (July 31, 2019). We drop loans from individuals sampled for Finlit who did not complete the IVR. Within each treatment group, the intervention was rolled out randomly in daily batches of varying sizes, over the period July 31, 2019 to August 16, 2019. For each graph, loans on the left of the red line were due after the individual received the treatment, whereas loans on the right of the red line were due before the treatment. This means that if there was a treatment effect, we'd expect the on-time repayment to be more likely to the left of the red line, and interest rate conditional on full repayment to be lower to the left of the red line. For figures showing "Fees paid" we only keep loans fully paid (either on time or late, N=2,461 loans).

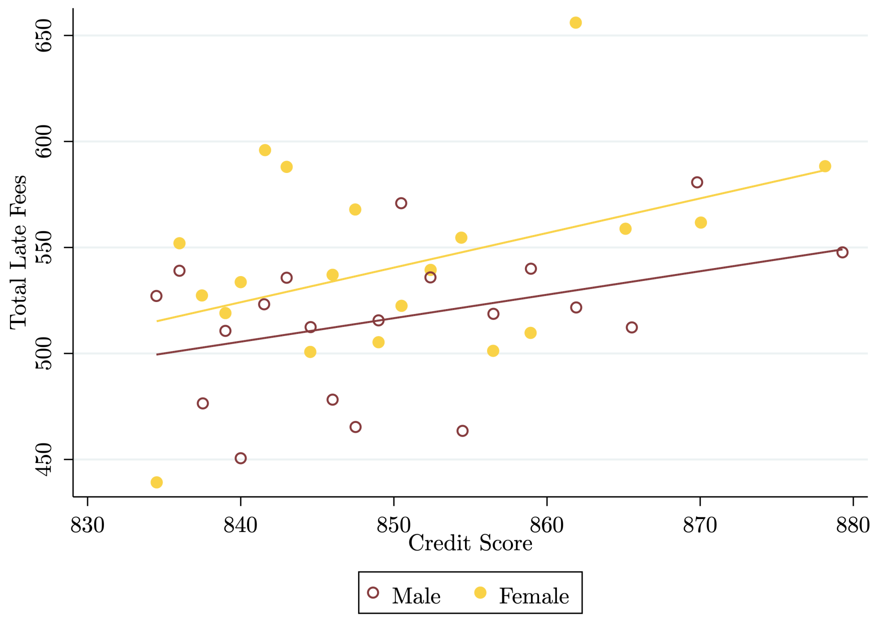
Figure 5: Patterns of Borrowing



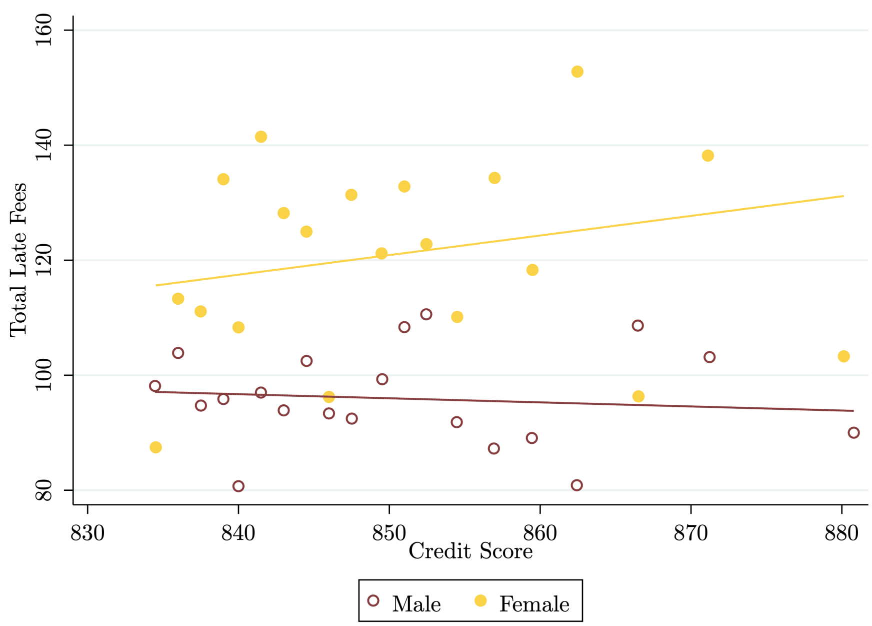
Notes: Data Source: Administrative Data. Unit of observation: individual user eligible for loan from Kutchova and included in Kutchova relaunch (N1, N2, E1 and E2). Sample limited to those who have borrowed at least once between July 2019 and May 2020 (N=11,828). Top panel shows the distributions of the total number of loans taken and the number of loans repaid fully but late. Bottom panel shows the distributions of the total number of loans repaid fully on time and the total number of loans repaid fully but at least 15 days late, meaning that the borrowed paid at least 22.5% in late fees (2.5% official late fee + twice the 10% facilitation fee) in addition to the original 10% facilitation fee.

Figure 6: Who Pays Late Fees?

(a) Conditional on having borrowed at least once



(b) Unconditional



Notes: Binscatter plots with quadratic fit lines. Data source: Administrative data on Kutchova loans from new users (N1, N2) who received a credit score from the third party, obtained a score of 834 or above, and were granted a credit limit of MWK 1,000 (the "above threshold" sample for the RD analysis). We compute and plot the total late fees paid across loans taken, by credit score. Top panel only includes those who borrowed at least once. Bottom panel includes all eligible customers. P-value for slope coefficient is 0.051 for males and 0.044 for females.

Table 1: Administrative Data: Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All Mobile Money Users between Jan & Mar 2019			Sub-population Eligible for Kutchova as of July 2019			
	All	Female	Male	All	Female	Male	P-Val Female = Male
Panel A. KYC Data							
Age Bracket: 18-24	0.17	0.18	0.16	0.13	0.18	0.10	<0.001
Age Bracket: 25-39	0.49	0.50	0.48	0.61	0.64	0.60	<0.001
Age Bracket: 40-59	0.28	0.26	0.30	0.24	0.17	0.29	<0.001
Age Bracket: 60+	0.06	0.06	0.06	0.02	0.01	0.02	0.001
Female	0.41	1.00	0.00	0.36	1.00	0.00	.
Panel B. Mobile Money Usage (Jan to Mar 2019)							
Number of transactions	3.84	3.88	3.91	18.33	19.53	17.75	<0.001
Total value of cash outs (USD)	9.94	9.59	9.93	15.04	12.71	16.17	<0.001
% eligible for Kutchova as of July 2019	1.95	1.73	2.18	100.00	100.00	100.00	.
Panel C. Digital Credit Usage (Jul 2019 to May 2020)							
Ever took a Kutchova loan				0.44	0.43	0.45	0.010
Number of loans taken (if>0)				4.77	4.47	4.87	<0.001
Total value of loans taken (USD) (if>0)				18.26	14.46	19.76	<0.001
Loan-level information							
Loan amount (USD)				4.07	3.30	4.35	<0.001
% of principal paid back				104.69	103.17	105.16	<0.001
Full, on time repayment				0.38	0.35	0.40	<0.001
% of principal paid back if on-time				110.35	110.31	110.37	0.606
Full, late repayment				0.47	0.49	0.46	<0.001
% of principal paid back if late				126.62	126.65	126.66	0.977
Non-zero, but incomplete repayment				0.04	0.04	0.04	0.056
% of principal paid back if incomplete				37.68	38.03	37.27	0.657
Zero repayment				0.11	0.13	0.11	<0.001
Number of loans				55,601	16,604	33,861	
Number of individuals	1,369,157	499,497	717,957	26,648	8,654	15,643	

Notes: Panels A and B present "Know your customer" (KYC) and mobile-money usage data which we obtained from Airtel in 2019. The sample includes all mobile money users who were active at least once in the 3 months prior to crerdit scoring (January and March 2019). It excludes customers eligibile for Kutchova who were excluded by Airtel from the relaunch (groups E3, N3 and N4). Panel C presents data on Kutchova borrowing behavior among those eligible for the period July 2019-May 2020, either because they were existing *Kutchova* customers, or because they received a credit score of 834 or higher (excluding again E3, N3 and N4 customers). Monetary outcomes are winsorized at 1%. The number of observations for all users is larger than the sum for female and male users because gender information is missing for some users. The gender information in KYC administrative data does not always reflect the gender of the user. The registered gender in the KYC matches gender collected in the survey data for 85% of respondents.

Table 2: Survey Data: Other Sources of Credit

	(1) Digital Airtime Loans	(2) Family / Friends	(3) VSLA	(4) MFI / Bank	(5) ROSCA	(6) Money-lender
Number of Observations: N=3,996						
Took a loan from this source in the past 3 months	0.57	0.24	0.10	0.05	0.02	0.01
If yes: Total number of loans taken in the past 3 months	6.46	1.75	1.58	1.08	1.20	1.46
Information about last loan						
Amount borrowed (USD)	0.37	74.79	104.08	541.93	185.73	733.63
	(0.60)	(169.46)	(155.06)	(1,004.58)	(341.44)	(1,974.73)
Loan terms						
Repayment period in months (if any)	0.37	1.11	1.88	7.81	1.52	1.85
	(0.75)	(1.03)	(1.74)	(7.70)	(1.17)	(2.01)
Interest rate or fee (%)	11.15	5.96	21.02	18.77	4.27	35.60
	(11.72)	(14.75)	(16.81)	(17.18)	(9.06)	(27.27)
Observations (loans)	2,367	935	428	188	65	39
Loan purpose						
Airtime	0.98	0.01	0.00	0.00	0.00	0.00
Investment into business/home	0.01	0.39	0.68	0.77	0.72	0.48
Food	0.00	0.30	0.18	0.10	0.23	0.13
Household expenses	0.01	0.15	0.03	0.03	0.02	0.13
School fee	0.00	0.14	0.16	0.18	0.05	0.13
Emergency payments: deaths/medical	0.00	0.08	0.03	0.01	0.00	0.12

Data Source: Phone Survey Data with RD sample (a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000). Notes: The summary statistics shown are adjusted for sampling weights to be representative. Monetary outcomes are winsorized at the top 1%. Interest rate or fee includes 0 values if the loan had no interest and no fee. Standard deviations in parentheses for certain rows.

Table 3: RD Analysis: Take-up of Digital Credit

	(1)	(2)	(3)	(4)	(5)	(6)
	Borrowed from Kutchova			Amount borrowed (USD)		
	Full Sample	Survey Sample		Full Sample	Survey Sample	
	Since July 2019	Since July 2019	In 3 Months Prior to Survey	Since July 2019	Since July 2019	In 3 Months Prior to Survey
Above credit eligibility threshold	0.34	0.38	0.13	1.77	2.21	0.54
	(0.02)	(0.03)	(0.02)	(0.19)	(0.28)	(0.09)
	{<0.001}	{<0.001}	{<0.001}	{<0.001}	{<0.001}	{<0.001}
Observations	10,768	3,996	3,996	10,768	3,996	3,996
Mean (non-eligible)	0.0020	0.0030	0.0020	0.0140	0.0210	0.0080
Mean (eligible)	0.36	0.41	0.13	2.16	2.48	0.63

Data source: Administrative data for mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000 (excluding groups N3 and N4). Notes: We use the "rdrobust" command in Stata. The running variable is the rescaled "predicted profit" variable constructed by the third party in charge of credit scoring. Analysis in columns 2, 3, 5 and 6 is restricted to the sample who completed the survey, and sampling weights are applied. We control for the following covariates available in the administrative dataset: gender, age bracket dummies, urban vs. rural, whether the user owns mutiple SIM cards, and whether the respondent was automatically enrolled in mobile money upon SIM card registration. Missing values for covariates are replaced by 0 and indicated by a dummy. Monetary outcomes are reported in USD and winsorized at 1%. Standard errors in parentheses, p-values in curly brackets.

Table 4: RD Analysis: Usage of Credit Across All Sources (Past 3 Months)

	(1)	(2)	(3)	(4)	(5)	(6)
	=1 if took		Number of loans			Total Amount
	Kutchova	Any Loan	Digital Airtime	Friends / Family	VSLA / ROSCA	Borrowed (USD)
Above credit eligibility threshold	0.12	0.15	1.62	0.13	0.02	2.22
	(0.03)	(0.05)	(0.89)	(0.12)	(0.05)	(5.94)
	{<0.001}	{0.006}	{0.068}	{0.251}	{0.749}	{0.708}
Observations	2,891	2,855	2,587	2,891	2,896	2,855
Mean (non-eligible)	0.0120	0.5890	4.5100	0.4470	0.1750	30.2110
Mean (eligible)	0.16	0.71	5.23	0.42	0.17	30.42

Data Source: Phone Survey Data with RD sample (a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000). Sample limited to those administered version 2 (=RD) of the survey since version 1 did not include information on past three months (only last loan). Sampling weights applied. We use the "rdrobust" command in Stata. The running variable is the rescaled "predicted profit" variable constructed by the third party in charge of credit scoring. We control for the same covariates available in the administrative dataset as in Table 3, and additionally control for the covariates from the survey shown in Table A2, region, and shocks experienced in the past 3 months. Notes: Monetary outcomes are winsorized at 5%. The amounts are reported in USD and include all borrowing in the past 3 months. "Total amount borrowed" excludes very uncommon sources such as moneylenders and MFIs. Standard errors in parentheses, p-values in curly brackets.

Table 5: RD Analysis: Financial Security

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Financial Security (higher value is higher well-being)						
	=1 if satisfied with financial well-being	Degree of Preparation for Future Emergencies (in SD)	Index of Ability to Pay for Non-food Expenses (in SD)	Food Security Index (in SD)	Used Digital Loan to Cope with Shock	Total Savings (USD)	Liquid Savings (USD)
Above credit eligibility threshold	0.124	0.060	0.076	-0.029	0.001	5.016	-11.295
	(0.041)	(0.079)	(0.079)	(0.085)	(0.002)	(14.769)	(10.874)
	{0.002}	{0.447}	{0.339}	{0.738}	{0.661}	{0.734}	{0.299}
Observations	3,996	3,996	3,995	3,980	2,809	3,308	3,993
Mean (non-eligible)	0.549	-0.007	-0.001	-0.019	0.001	107.713	81.078
Mean (eligible)	0.603	0.125	0.150	0.029	0.003	122.681	82.604

Data Source: Phone Survey Data with RD sample (a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000). Notes: See Table 4 notes for information on the Stata command, controls, and running variable used. Sampling weights applied. Index of ability to pay for non-food expenses is derived from 4 variables: payments for health expenditures, bill payments, school fees and ability to help family/friends in time of need. Food security index is derived form 4 variables: relying on less expensive foods, limiting meal sizes, reducing number of meals and borrowing food. We compute indices using weighted averages and standardizing against the non-eligible group. "Total Savings" is the value reported by the respondent when asked: "How much money did you have in savings (across all your saving places) at the end of last month?". "Liquid Savings" sums up reported savings across 5 saving methods (saving box, bank, mobile money, MFI/SACCO, VSLA). Monetary amounts are reported in USD and winsorized at 5%. Standard errors in parentheses, p-values in curly brackets.

Table 6: Kutchova Perceptions and Experiences Among Kutchova Borrowers

	(1) Mean (All)	(2) Mean (Males)	(3) Difference Between Females and Males	(4) P-value	(5) N
Panel A. Last Kutchova loan					
Why did you take out Kutchova instead of using your own money?					
Had the money but Kutchova was more accessible	0.238	0.220	0.041	0.31	534
Had money coming soon, but wanted to make the purchase immediatel	0.279	0.311	-0.075	0.09	534
I did not have the money but needed to take care of something	0.483	0.468	0.034	0.47	534
Last loan: At least one loan attempt failed first	0.184	0.193	-0.020	0.61	520
Panel B. Rejected loans					
Has a loan request ever been rejected even after multiple attempts?	0.200	0.245	-0.113	0.01	347
Last time you applied for Kutchova but didn't get a loan, what did you do instead?					
Borrowed from somewhere else	0.255	0.252	0.011	0.93	71
Took money from my own savings	0.147	0.180	-0.129	0.09	71
Reduced the expense	0.099	0.115	-0.064	0.49	71
I did not incur the expense	0.377	0.344	0.125	0.36	71
Panel C. Self-reported satisfaction					
Have you ever regretted taking out a Kutchova loan? Yes	0.116	0.092	0.057	0.05	535
Do you like the Kutchova product? Yes	0.898	0.899	-0.002	0.94	533
Reasons for liking Kutchova (multiple choice)					
I get money immediately	0.719	0.726	-0.018	0.66	537
Get loan on my phone	0.259	0.278	-0.046	0.30	537
Low interest rate compared to other lenders	0.136	0.128	0.019	0.54	537
No one else knows about how much I have borrowed	0.083	0.077	0.014	0.55	537
Reasons for disliking Kutchova (multiple choice)					
Tempted to take unnecessary loans	0.093	0.106	-0.028	0.29	537
Interest higher than other options	0.090	0.096	-0.014	0.60	537
Loan repayment period is short	0.132	0.141	-0.021	0.53	537
Involves withdrawal charges	0.074	0.082	-0.017	0.49	537
Panel D. Awareness of Kutchova Terms					
Knows fee/interest rate	0.286	0.281	0.012	0.81	437
Knows after how many days loan is due	0.472	0.488	-0.036	0.51	438
Knows there is a fee if late	0.456	0.466	-0.022	0.68	437
What happens if loan not repaid?					
Don't know	0.394	0.349	0.104	0.04	440
Airtel deducts money from my mobile	0.096	0.099	-0.009	0.79	440
Interest accumulates	0.286	0.302	-0.036	0.46	440
Airtel disables sim card	0.073	0.107	-0.078	0.08	440
Nothing	0.023	0.022	0.003	0.85	440

Data Source: Survey with RD sample (a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000). Sample limited to eligible users who borrowed from Kutchova at least once. Note: The information in Panel B was added to the survey mid-way and hence is only available for a subsample of respondents. The information in panel D "Awareness of Kutchova Terms" is only displayed for respondents who did not receive the Finlit treatment. Sampling weights applied.

Table 7: RCT Analysis: Knowledge

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				What happens if you don't pay back a Kutchova loan?				
	Knows Fee/ Interest Rate on Kutchova Loans	Knows After How Many Days Loan is Due	Knows Late Repayment is Penalized by Fee	Don't Know	Interest Accumulates	Airtel Deducts Money from my Mobile	Get Reported to Credit Bureau	Credict Access Reduced
Finlit	0.179	0.160	0.151	-0.154	0.012	0.085	0.025	0.021
	(0.026)	(0.025)	(0.025)	(0.026)	(0.020)	(0.023)	(0.009)	(0.008)
	{<0.001}	{<0.001}	{<0.001}	{<0.001}	{0.540}	{<0.001}	{0.004}	{0.011}
Salience	0.054	0.054	0.059	-0.057	0.009	0.019	-0.001	0.003
	(0.025)	(0.025)	(0.024)	(0.027)	(0.020)	(0.022)	(0.007)	(0.008)
	{0.031}	{0.028}	{0.013}	{0.034}	{0.642}	{0.404}	{0.846}	{0.674}
InfoSMS	0.039	0.037	0.027	-0.024	0.002	0.035	-0.009	0.007
	(0.031)	(0.030)	(0.030)	(0.033)	(0.024)	(0.029)	(0.007)	(0.010)
	{0.208}	{0.211}	{0.368}	{0.474}	{0.924}	{0.217}	{0.233}	{0.489}
Observations	3,304	3,307	3,303	3,321	3,321	3,321	3,321	3,321
Mean of Control	.296	.354	.277	.536	.158	.227	.016	.018
P-val Finlit=Salience	<0.001	<0.001	<0.001	<0.001	0.860	0.001	<0.001	0.019
P-val Finlit=InfoSMS	<0.001	<0.001	<0.001	<0.001	0.636	0.061	<0.001	0.139

Data source: Phone survey data conducted in October 2019 with RCT survey sample (a subset of mobile money users eligible for Kutchova as of the July 2019 relaunch). Unit of observation: individual user. Notes: All regressions include sampling weights and control for stratification variables from the administrative data (the relaunch batch to which the user was assigned (N1, N2, E1, or E2), whether the respondent was automatically enrolled in mobile money upon SIM card registration, quantiles for the year of birth, whether the respondent was eligible for loans higher than MWK 1,000, gender, whether the user is classified as "urban" in the KYC data, and whether the respondent had more than one SIM card), as well as the intervention batch to which the user was assigned (the intervention was rolled out randomly in daily batches of varying sizes, over the period July 31, 2019 to August 16, 2019), credit score, gender (survey data), region (survey data), and whether the user took out a Kutchova loan in the pre-treatment period (July 2019). Robust standard errors in parentheses, p-values in curly brackets.

Table 8: RCT Analysis: Impact of Finlit on Take-up of Kutchova Product

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Before Treatment (Balance Test)			0-3 Months After Treatment			3-9 Months After Treatment		
	Took Loan	Number of Loans	Amount	Took Loan	Number of Loans	Amount	Took Loan	Number of Loans	Amount
Finlit	0.019	0.028	0.062	0.040	0.134	0.366	0.018	0.121	0.384
	(0.007)	(0.010)	(0.036)	(0.007)	(0.024)	(0.085)	(0.008)	(0.043)	(0.205)
	{0.008}	{0.007}	{0.087}	{<0.001}	{<0.001}	{<0.001}	{0.022}	{0.005}	{0.060}
Salience	0.009	0.014	0.050	0.013	0.026	0.106	0.002	0.032	0.057
	(0.007)	(0.010)	(0.036)	(0.007)	(0.023)	(0.084)	(0.008)	(0.043)	(0.202)
	{0.197}	{0.155}	{0.162}	{0.086}	{0.266}	{0.207}	{0.820}	{0.456}	{0.776}
InfoSMS	-0.003	0.001	-0.011	0.009	0.022	0.133	-0.007	0.001	0.028
	(0.008)	(0.011)	(0.039)	(0.008)	(0.025)	(0.091)	(0.008)	(0.046)	(0.219)
	{0.739}	{0.927}	{0.777}	{0.253}	{0.362}	{0.143}	{0.380}	{0.989}	{0.899}
Observations	26,467	26,467	26,467	26,467	26,467	26,467	26,467	26,467	26,467
Mean of Control	.226	.287	.941	.253	.615	2.05	.293	1.089	4.209
P-val Finlit=Salience	0.172	0.200	0.757	<0.001	<0.001	0.003	0.039	0.047	0.113
P-val Finlit=InfoSMS	0.005	0.018	0.065	<0.001	<0.001	0.012	0.003	0.012	0.111

Data Source: Administrative Kutchova data. Unit of observation: individual user. Notes: Sample includes all Airtel customers eligible for Kutchova as of the July 2019 relaunch. The Finlit and other treatments took place within the first two weeks of August 2019. The period 0-3 months after Treatment corresponds to the period for which survey data (shown in Table 7 and Table A5) was collected. All regressions control for the launch batch to which the user was assigned by Airtel (N1, N2, E1, or E2), the Finlit RCT intervention batch to which the user was assigned by the research team (the intervention was rolled out randomly in daily batches of varying sizes, over the period July 31, 2019 to August 16, 2019), the gender, credit score, whether the respondent was eligible for loans higher than MWK 1,000, whether the user owns multiple SIM cards, whether the user is classified as "urban" in the KYC data, and whether the respondent was automatically enrolled in mobile money upon SIM card registration. Columns 4-9 additionally control for whether the respondent took a loan during the pre-treatment period. Monetary outcomes are reported in USD and winsorized at 1%. Robust standard errors in parentheses, p-values in curly brackets.

Table 9: RCT Analysis: Loan-Level Outcomes

	(1)	(2)	(3)	(4)	(5)
	Percentage of Total Principal Repaid	Loan Fully Paid Back on Time	Loan Fully Paid Back Late	Loan Partially Paid Back	Zero Repayment
Finlit	0.009	0.016	-0.007	0.002	-0.011
	(0.006)	(0.006)	(0.007)	(0.002)	(0.004)
	{0.091}	{0.013}	{0.290}	{0.497}	{0.010}
Salience	-0.000	0.017	-0.015	0.001	-0.004
	(0.006)	(0.007)	(0.007)	(0.002)	(0.004)
	{0.930}	{0.009}	{0.028}	{0.580}	{0.376}
InfoSMS	0.008	-0.013	0.016	-0.002	-0.002
	(0.006)	(0.007)	(0.007)	(0.002)	(0.005)
	{0.188}	{0.067}	{0.027}	{0.540}	{0.723}
Observations	40,338	44,907	44,907	44,907	44,907
Mean of Control	1.057	0.392	0.466	0.031	0.112
P-val Finlit=Salience	0.073	0.848	0.230	0.910	0.089
P-val Finlit=InfoSMS	0.815	<0.001	0.001	0.205	0.039

Data Source: Administrative Kutchova data. Unit of observation: Kutchova loan. Notes: Sample includes all loans made *after* the rollout of the RCT interventions, by individuals eligible for Kutchova as of the July 2019 relaunch. The Finlit and other treatments took place within the first two weeks of August 2019. The period 0-3 months after Treatment corresponds to the period for which survey data (shown in Table 7 and Table A5) was collected. All regressions control for the relaunch batch to which the user was assigned (N1, N2, E1, or E2), the intervention batch to which the user was assigned (the intervention was rolled out randomly in daily batches of varying sizes, over the period July 31, 2019 to August 16, 2019), whether the user took out a Kutchova loan during the pre-treatment period (July 2019), the loan amount, gender, credit score, whether the respondent was eligible for loans higher than MWK 1,000, whether the user owns multiple SIM cards, whether the user is classified as "urban" in the KYC data, and whether the respondent was automatically enrolled in mobile money upon SIM card registration. Robust standard errors in parentheses, p-values in curly brackets.

Table 10: RCT Analysis: Impact of Finlit by User Type (User-Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Existing Borrowers (E1, E2)				Newly Eligible (N1, N2)			
	Total Amount Borrowed (0-9 months)	Late Fees paid (% of total borrowed) (0-9 months)	Late Fees paid (Total)	After 9 months: In Default (Ineligible)	Total Amount Borrowed (0-9 months)	Late Fees paid (% of total borrowed) (0-9 months)	Late Fees paid (Total)	After 9 months: In Default (Ineligible)
Finlit	1.170	-0.003	0.078	0.008	0.455	-0.001	0.033	0.017
	(1.264)	(0.004)	(0.108)	(0.019)	(0.176)	(0.003)	(0.014)	(0.007)
	{0.355}	{0.377}	{0.469}	{0.668}	{0.010}	{0.750}	{0.023}	{0.011}
Salience	-0.297	-0.001	-0.033	-0.002	0.142	0.000	0.007	0.011
	(1.254)	(0.004)	(0.107)	(0.019)	(0.172)	(0.003)	(0.015)	(0.007)
	{0.813}	{0.743}	{0.759}	{0.899}	{0.408}	{0.969}	{0.652}	{0.111}
InfoSMS	0.327	-0.003	0.088	0.003	0.095	0.006	0.013	-0.001
	(1.271)	(0.004)	(0.111)	(0.019)	(0.179)	(0.003)	(0.016)	(0.007)
	{0.797}	{0.451}	{0.428}	{0.868}	{0.595}	{0.047}	{0.418}	{0.882}
Observations	4,553	3,039	4,553	4,553	21,914	6,886	21,914	21,914
Mean of Control	21.701	.135	2.023	.282	3.048	.146	.314	.149
P-val Finlit=Salience	0.246	0.580	0.302	0.580	0.086	0.718	0.075	0.331
P-val Finlit=InfoSMS	0.509	0.919	0.928	0.806	0.061	0.022	0.206	0.013

Data Source: Administrative Kutchova data. Unit of observation: individual user. Sample include all Airtel customers eligible for loans as of the July 2019 relaunch. The Finlit and other treatments took place within the first two weeks of August 2019. The period 0-3 months after Treatment corresponds to the period for which survey data (shown in Table 7 and Table A5) was collected. All regressions control for the relaunch batch to which the user was assigned (N1, N2, E1, or E2), the intervention batch to which the user was assigned (the intervention was rolled out randomly in daily batches of varying sizes, over the period July 31, 2019 to August 16, 2019), gender, credit score, whether the respondent was eligible for loans higher than MWK 1,000, whether the user owns multiple SIM cards, whether the user is classified as "urban" in the KYC data, whether the respondent was automatically enrolled in mobile money upon SIM card registration, and whether the respondent took a loan during the pre-treatment period. The monetary amounts are reported in USD and winsorized at 1%. Robust standard errors in parentheses, p-values in curly brackets.

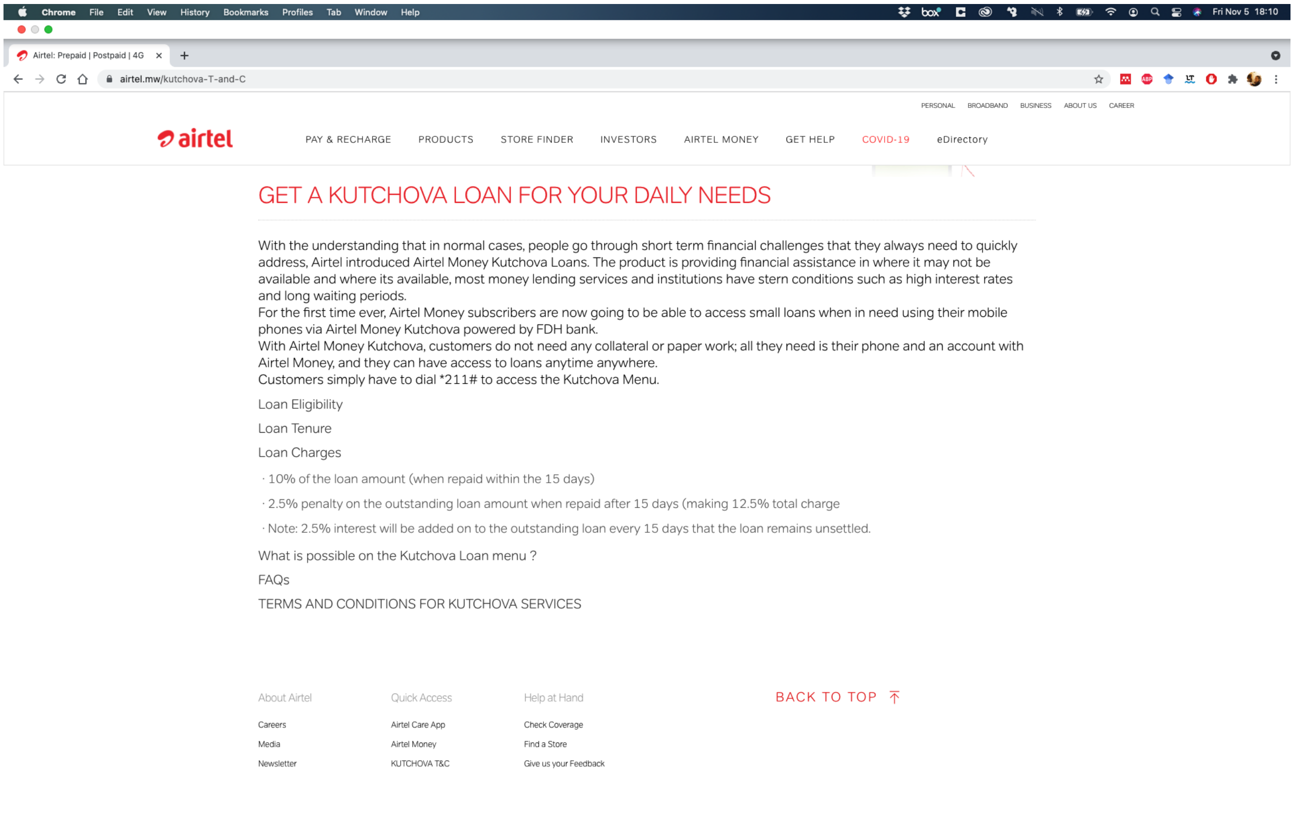
Table 11: Covariates of Aberrant Borrowing Behavior

	(1) Total Late Fees Paid (MWK)	(2) Borrowed More Than Once	(3) Paid Late Fees More Than Once	(4) Paid Max Late Fees at Least Once	(5) Repaid ≥ 1 Loan Late On the Due Date	(6) Borrowed on July 23/24 2019 (Marketing Days)
Panel A: Admin Characteristics						
Female	0.678	-0.012	-0.005	-0.003	-0.004	-0.003
	(6.142)	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)
Age Bracket: 18-24	37.326	0.060	0.027	0.021	0.027	0.022
	(8.361)***	(0.010)***	(0.009)***	(0.009)**	(0.009)***	(0.008)***
Age Bracket: 60+	-75.771	-0.050	-0.051	-0.095	-0.047	-0.058
	(16.161)***	(0.025)**	(0.019)***	(0.015)***	(0.019)**	(0.012)***
Multiple sim cards	9.175	-0.007	-0.006	0.005	-0.013	0.013
	(7.751)	(0.009)	(0.008)	(0.008)	(0.008)*	(0.007)*
Opened mobile account when registered sim	17.893	0.015	0.010	0.011	0.012	0.011
	(5.862)***	(0.007)**	(0.006)	(0.006)*	(0.006)*	(0.005)**
Total Cash Out (/10,000)	0.817	0.001	0.000	0.000	0.001	0.001
	(0.385)**	(0.000)	(0.000)	(0.000)	(0.000)*	(0.000)*
Total Cash In (/10,000)	-2.107	-0.002	-0.002	-0.001	-0.002	-0.001
	(0.317)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
P2P Transfers Sent (/10,000)	1.100	0.001	0.001	0.002	0.001	-0.001
	(0.597)*	(0.001)*	(0.001)**	(0.001)**	(0.001)	(0.000)***
P2P Transfers Received (/10,000)	0.185	-0.000	0.000	-0.000	0.000	0.002
	(1.151)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)*
Observations	15,113	15,035	15,113	15,113	14,260	15,113
Mean	194.835	.241	.157	.153	.146	.1
Panel B: Survey Characteristics						
Number of Years of Education	8.230	0.011	0.009	0.006	0.005	0.001
	(2.035)***	(0.003)***	(0.002)***	(0.002)**	(0.003)*	(0.002)
Self-Employed	-17.116	-0.010	-0.013	-0.014	0.001	-0.003
	(13.298)	(0.017)	(0.014)	(0.014)	(0.015)	(0.012)
Monthy Income in MWK (/10,000)	0.645	0.001	0.001	0.001	0.001	-0.000
	(0.489)	(0.001)	(0.001)	(0.001)**	(0.001)*	(0.000)
Has Electricity	14.332	0.019	0.015	0.015	0.011	0.018
	(14.918)	(0.019)	(0.016)	(0.016)	(0.018)	(0.014)
Owns House	-26.168	-0.011	-0.000	-0.021	-0.019	-0.009
	(13.186)**	(0.017)	(0.015)	(0.014)	(0.016)	(0.012)
Household Size	-0.687	-0.004	0.002	-0.002	-0.002	-0.004
	(3.010)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Observations	3,168	3,164	3,168	3,168	3,055	3,168
Mean	226.49	.288	.185	.173	.218	.114

Data source: Administrative data from Airtel (Panels A and B) and phone survey data, pooling October 2019 (RCT survey) and March 2020 (RD survey) respondents (Panel B). Notes: Sample restricted to those newly eligible for Kutchova as of July 2019 (groups N1 and N2) and given a credit limit of MWK 1,000. Sampling weights applied in Panel B. Missing values for the "Know-your-Customer" variables (female, age bracket, multiple SIM cards and whether the user opened a mobile account upon the SIM registration) are replaced by the mean value. Column 5 has less observations than other columns due to missing information on the loans due date. All regressions include controls for RCT treatment assignment. "Repaid ≥ 1 loan late on the due date" is a dummy indicating if a user ever repaid a loan on the due date but missed the due hour and was charged a late penalty fee (either on the 15th day after disbursal, or on the 30th day). Monetary outcomes are winsorized at 5% and reported in MWK/10,000). A Kutchova loan is considered "late" if it is not repaid within 15 days of disbursal. A 12.5% late fee (2.5% penalty fee + 10% facilitation fee) is applied after 15 days, in addition to the original 10% facilitation fee. If the loan is still outstanding after 15 additional days, a 10% facilitation fee is re-applied. After 45 late days, the loan is declared as defaulted, no further fees are charged and Airtel attempts to recover the outstanding amount automatically using funds from the user's Kutchova Save account. The maximum late fee amount is 32.5%. Robust standard errors in parentheses. Stars indicate significance level (*** 1 % level, ** 5% level, * 10% level).

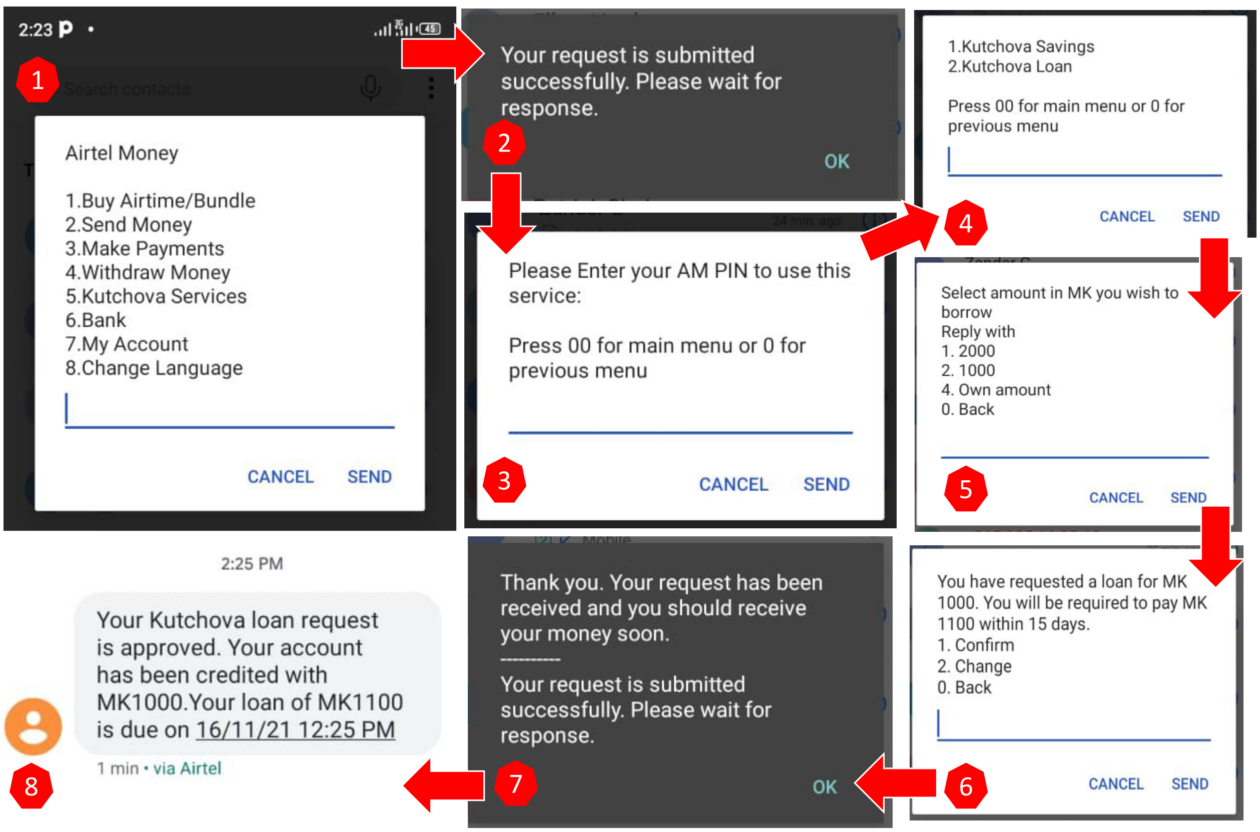
Appendix A: Appendix Figures and Tables

Figure A1: Kutchova Loan Terms & Conditions from Airtel's Website



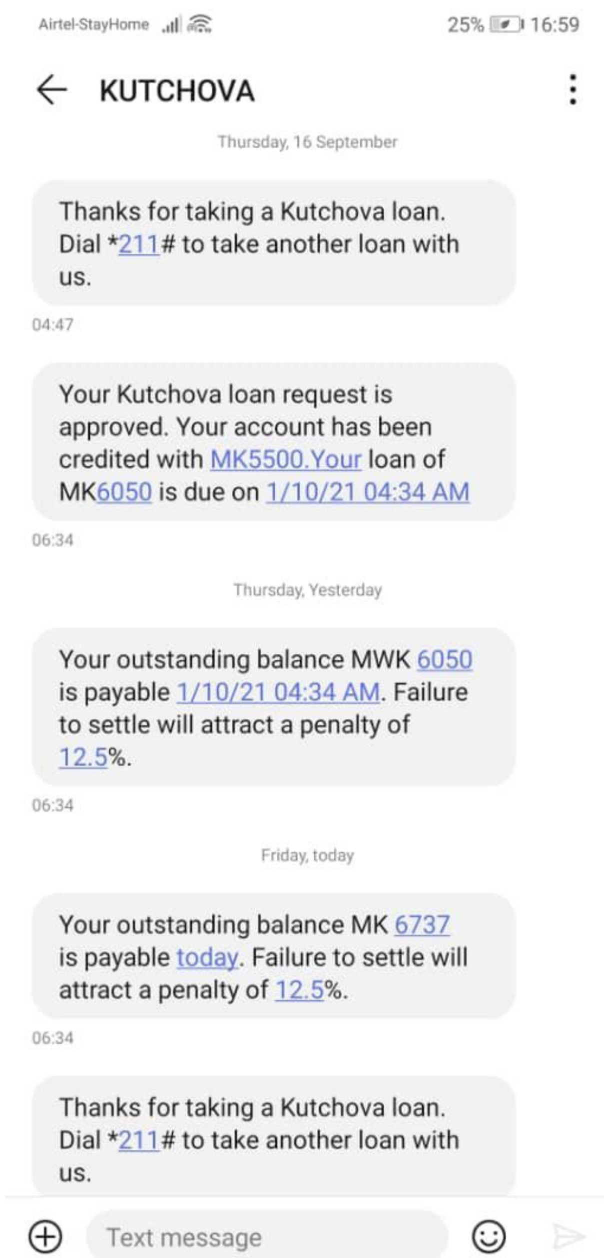
Notes: Screenshot taken on November 5th, 2021 on Airtel's website. The Terms and Conditions mention a late fee of 2.5%. This is identical to what was on the website at the time of the launch. Customers receive a text from Airtel around 24 hours before the loan's due date explicitly stating the total late penalty is 12.5% (see Figure A3).

Figure A2: Requesting & Receiving a Kutchova Loan



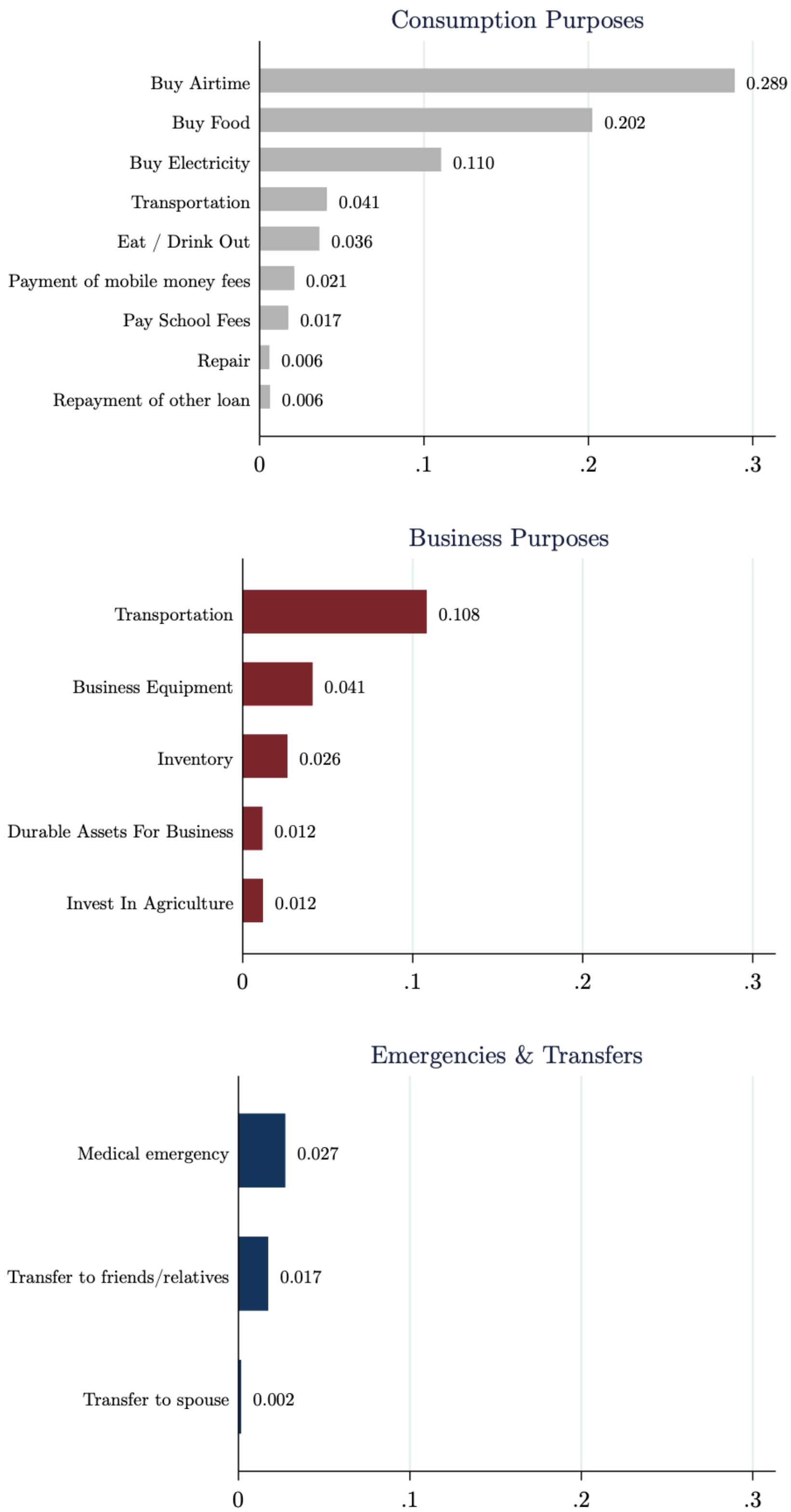
Notes: Screenshots for an individual who was eligible for, applied, and received a MWK 1,000 Kutchova loan on October 29th, 2021. The user dialed *211# to access the Airtel Money Menu. The user started the loan application at 2.23pm and was credited the MWK 1,000 by 2.25pm the same day. The user was not shown the terms and conditions during the application.
Acceptance of the Terms and Conditions is implied when customers request a loan. See T&C (website https://airtel.mw/kutchova-T-and-C) item 2.3:
"You will be deemed to have read, understood and accepted these Terms and Conditions:
2.3.1. upon clicking on the "Accept" option on the Kutchova Menu requesting you to confirm that you have read, understood and agreed to abide by these Terms and Conditions; and/or
2.3.2. by using or continuing to use and operate the Kutchova services."

Figure A3: Late Fees Warning Text from Airtel



Notes: Screenshot taken on October 1st, 2021. 22 hours before the loan due time, customers receive a warning text from Airtel indicating that the late fee penalty would be 12.5%. The customer failed to repay on time, so Airtel added the 12.5% fee and sent a text message shortly after to encourage the customer to repay that day to avoid an additional penalty (though the language is not clear that a penalty fee has already been applied). The customer cleared their balance in response, on the due day but too late to avoid fees.

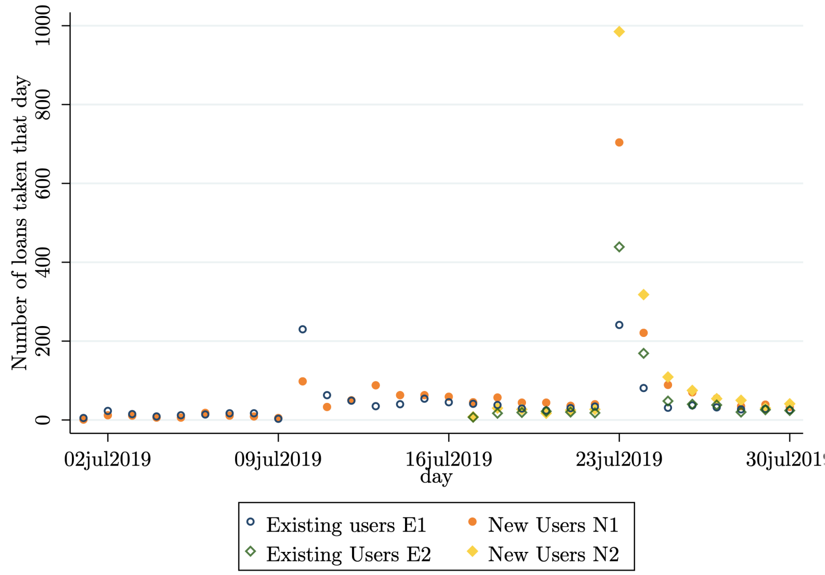
Figure A4: What was your last Kutchova loan for?



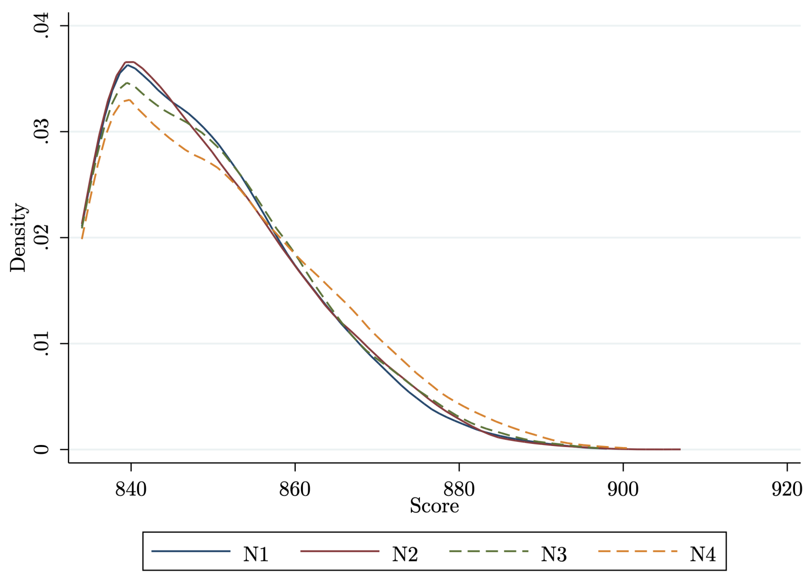
Notes: Data source: RCT Survey. Sampling weights applied.

Figure A5: July 2019 Gradual Relaunch

(a) Sequential Launch



(b) Score Distribution by New User Launch Group



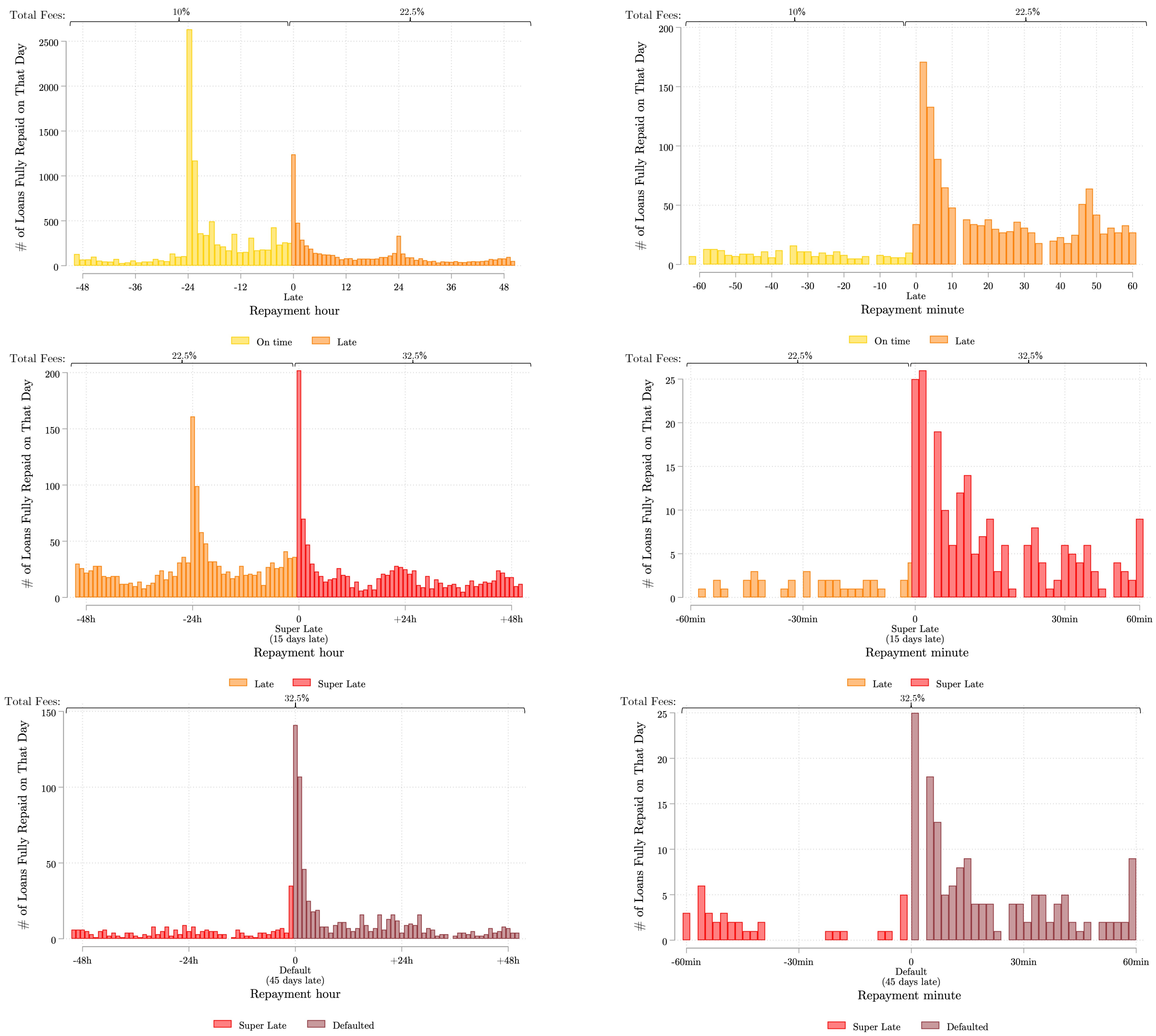
Notes: Data Source: Administrative Data.

Panel a: Existing users were split by Airtel into 3 groupss (E1, E2 and E3). New users deemed eligible (i.e., scored ≥ 834 by third party) were split by Airtel into 4 groups (N1, N2, N3 and N4). They were scheduled to be granted access to Kutchova in week 1, 2, 3 and 4 of July 2019, respectively. Ultimately, only groups N1, E1, N2 and E2 were granted access. All our analyses exclude groups N3 and N4. Sample restricted to loans taken by users from groups E1, E2, N1 and N2.

On July 23, 2019, Airtel conducted a big push of the Kutchova product via SMS among eligible customers. This led to a spike in borrowing on that day and the following day.

Panel b: Sample restricted to new users who received a credit score from the third party, were deemed eligible for a Kutchova loan (N1, N2, N3 and N4) and had a credit limit of MWK 1,000.

Figure A6: Repayment Patterns & Auto Recovery



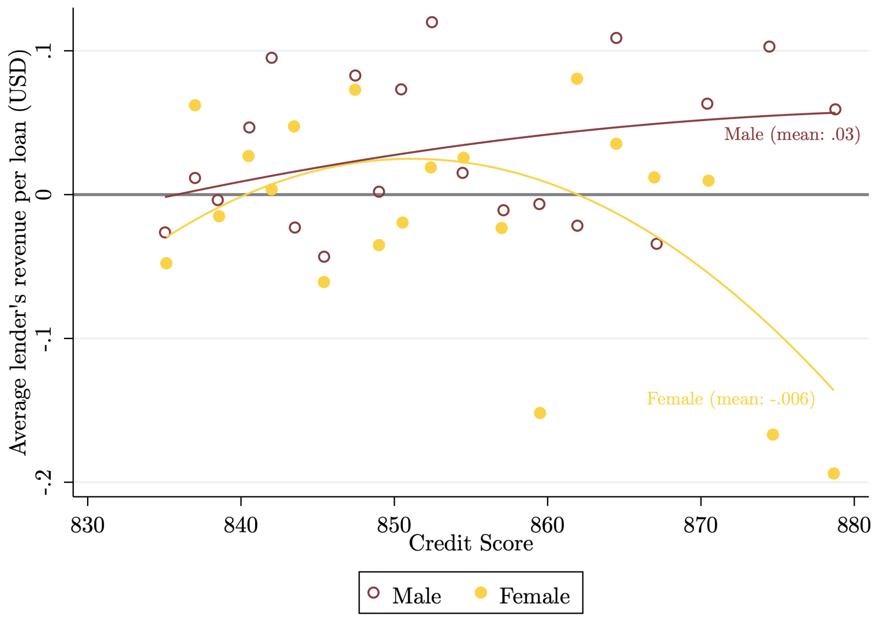
(a) Repayments Within 48h of Due Hour

(b) Repayments Within 60min of Due Minute

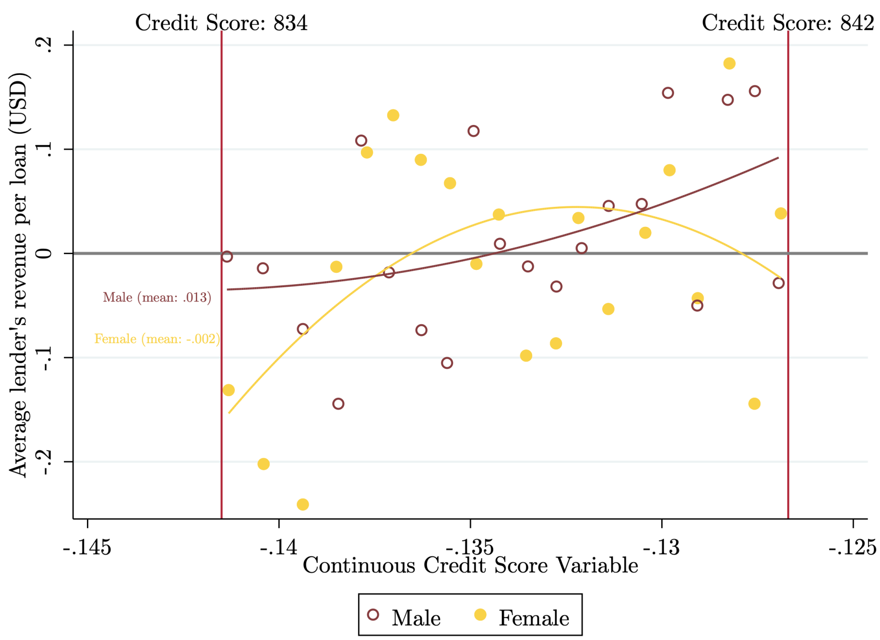
Notes: Source: Administrative Data on Kutchova loans obtained from Airtel. Unit of observation: Loan. Loans taken in the 8 weeks preceding May 20, 2020 (when the data was shared with the research team) are dropped since some borrowers take up to 8 weeks to repay in full. The final sample is composed of almost 44,000 loans. After the due date (day 0), 15 days after the loan's disbursal, a loan is considered "late". A 12.5% late fee is applied after 15 days, in addition to the original 10% facilitation fee. Airtel attempts to recover the outstanding amount automatically using funds from the user's Kutchova Save account. If the loan is still outstanding after 15 additional days (day 15), a 10% fee is re-applied to the unpaid portion of the loan. After 45 late days (day 45), a loan is declared defaulted, no further fees are charged and Airtel attempts to recover the outstanding amount automatically using funds from the user's Kutchova Save account. The maximum late fee amount is 32.5%. According to Kutchova's FAQ 8 (link: https://airtel.mw/kutchova-T-and-C), Airtel can start attempting autorecovery after 7 days (day -9 here): "The system will start to auto recover the loan after 7 days. If the full amount is not recovered within 15 days, an extra charge of 2.5% of the outstanding loan will be applied."

Figure A7: Do Credit Scores Predict Profitability for the Bank?

(a) Large range of credit scores

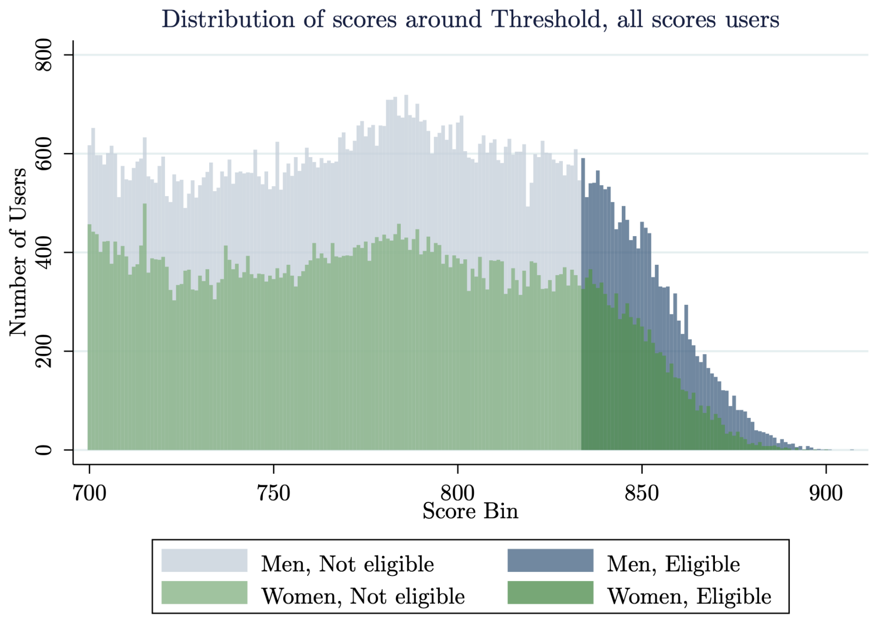


(b) Zooming in: within 8 points of eligibility threshold (RD Bandwidth)



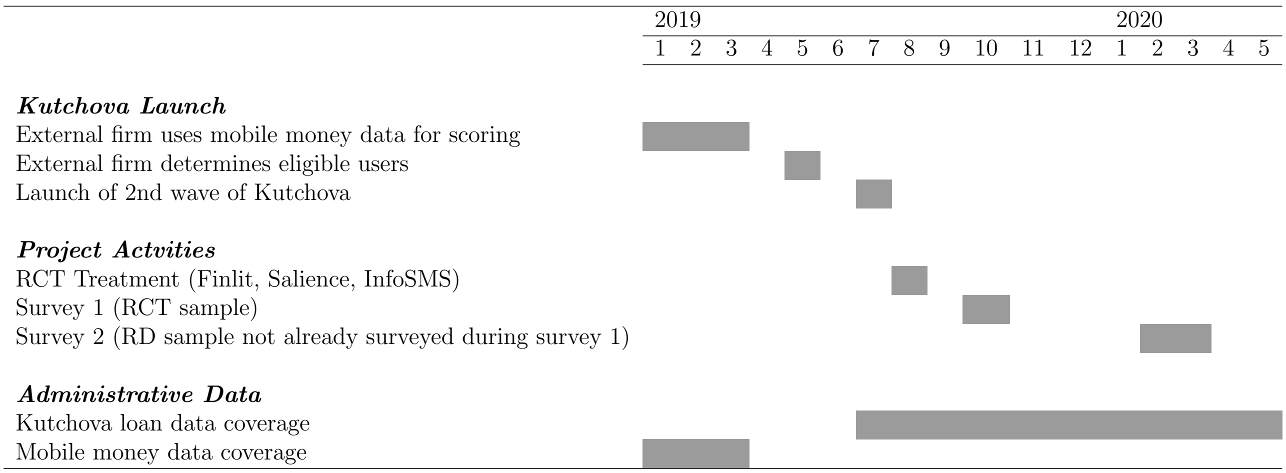
Notes: Binscatter plots. Data source: Administrative data on Kutchova loans from new users (N1, N2) who received a credit score from the third party. Panel a: We compute and plot the average bank's profit across loans, for 20 quantiles of the Credit Score distribution from the eligibility threshold (834 or above) to the 95th percentile (882). We do this separately by borrower gender. Lines represent quadratic fits. Panel b: We limit ourselves to loans by borrowers within the bandwidth used in the RD analysis (834 to 842). We compute and plot the average bank's profit across loans, for 20 quantiles of the "predicted profit" variable distribution.

Figure A8: Distribution of Scores: all users below threshold and only new users who qualified for 1000 loan above threshold, scores > 700



Notes: The figure includes all scored users below the threshold and all new users (N1-N4) who were determined to be eligible for a MWK 1,000 loan. The figure excludes existing users (E1, E2, and E3), those with a credit score under 700, and those who qualified for a loan >MWK 1,000.

Figure A9: Timeline



Notes: Timeline of Kutchova launch, project activities, and months for which we have Airtel administrative data (Kutchova loan data or mobile money data).

Figure A10: First-stage for Finlit RCT, by Gender

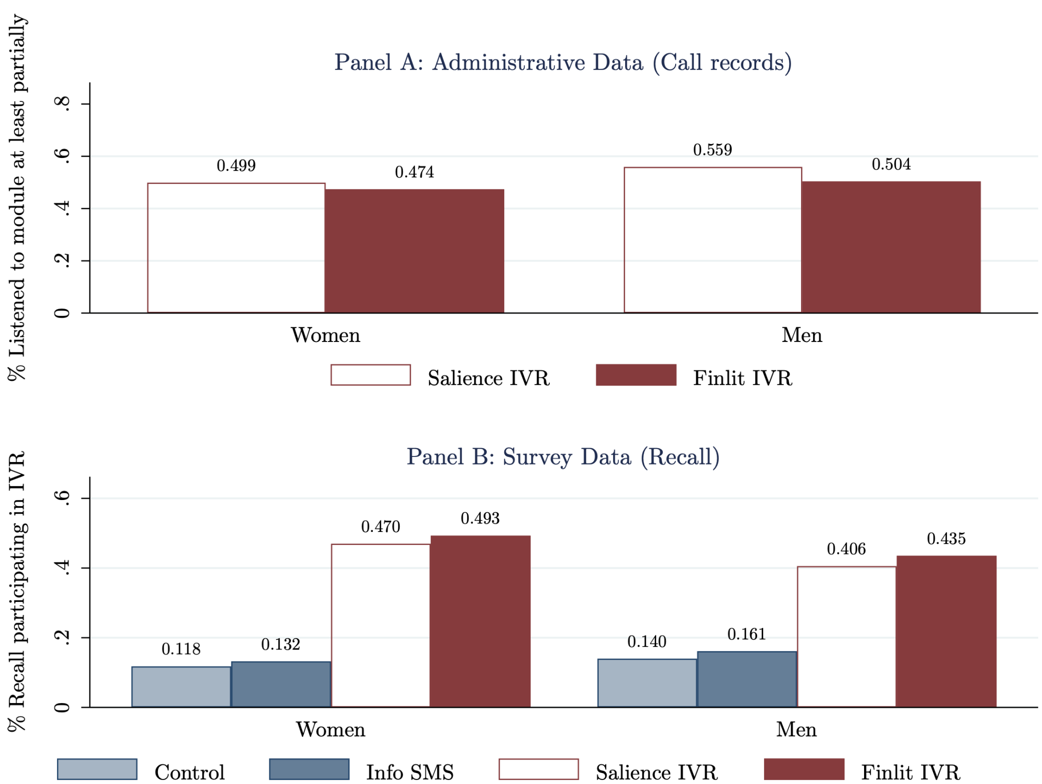
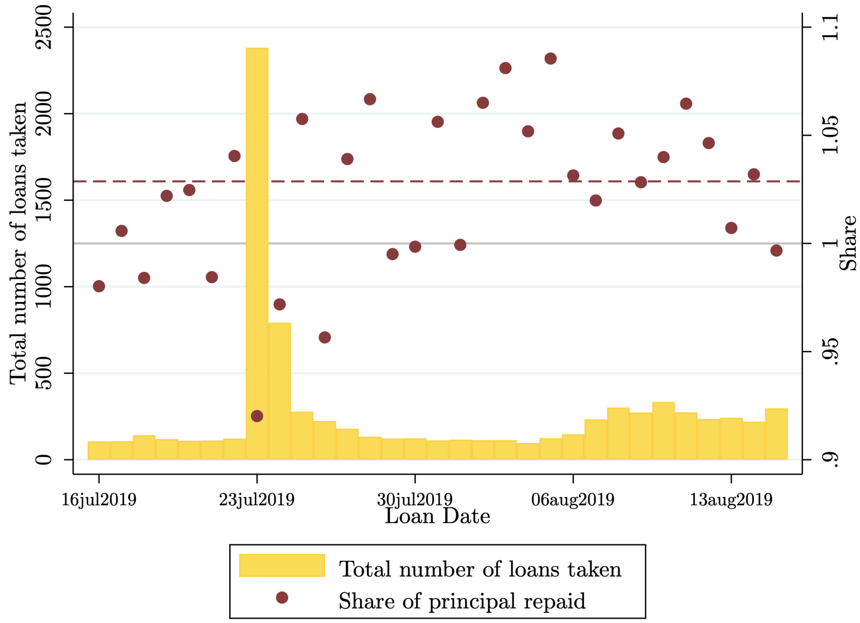


Figure A11: Repayment Levels by Day, July 16 to August 15, 2019



Notes: Dashed line shows the average share of principal repaid for the period shown, excluding loans taken on July 23 or July 24. The share of principal repaid among loans taken on July 23 is 10 percentage points lower (p-value<0.001) than the average share repaid across all other days shown, and 8.6 percentage points lower (p-value<0.001) than the average in the preceding 7 days. The share of loans with zero repayment is 7.3 percentage points higher (p-value<0.001) among loans taken on July 23 compared to all other days shown, and 4.0 percentage points (p-value<0.001) higher than the preceding 7 days.

Table A1: RD: Survey Attrition and Balance on Baseline Administrative Variables if Surveyed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Attrition:	Balance if Surveyed:					
	Could not be Surveyed	Age (KYC)	Urban (KYC)	Total Cash Out	Total Cash In	P2P transfers Sent	P2P transfers Received
Panel A: Females							
Above threshold	-0.06	-2.50	0.05	8.67	1.46	-4.42	-0.71
	(0.05)	(1.12)	(0.06)	(16.15)	(18.09)	(12.19)	(7.10)
	{0.251}	{0.026}	{0.411}	{0.591}	{0.936}	{0.717}	{0.920}
Observations	2,759	1,860	1,860	1,860	1,860	1,860	1,860
Mean (non-eligible)	0.34	33.50	0.63	121.13	130.42	62.86	35.94
Mean (eligible)	0.30	32.23	0.65	133.74	141.34	67.00	41.09
Panel B: Males							
Above threshold	-0.03	-0.91	0.02	-0.27	-2.39	-18.39	-1.46
	(0.05)	(1.23)	(0.06)	(18.85)	(20.72)	(12.16)	(6.76)
	{0.550}	{0.457}	{0.685}	{0.988}	{0.908}	{0.130}	{0.829}
Observations	3,008	2,122	2,121	2,122	2,122	2,122	2,122
Mean (non-eligible)	0.29	36.57	0.53	133.25	159.41	86.09	39.13
Mean (eligible)	0.27	34.62	0.51	128.96	165.17	76.44	37.10

Data source: Administrative KYC and Mobile Money data provided by Airtel for users who were sampled for the RD survey (a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000). Notes: See Table 4 notes for information on the Stata command and running variable used. Mobile money transactions information shown in columns 4 to 7 correspond to the January-March 2019 period, the period used to determine Kutchova eligibility. For columns 2 to 7, the sample is restricted to users who could be surveyed. P2P stands for Peer-to-Peer. Monetary outcomes are reported in USD and winsorized at 1%. Sampling weights applied. Standard errors in parentheses, p-values in curly brackets.

Table A2: RD: Balance on Background Characteristics (Survey Measures)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Years of Education	Self-Employed	Monthly Income	HH Size	HH Head	Married	Owns House	Has Electricity
Panel A: Females								
Above threshold	-0.59	-0.06	-3.04	-0.11	-0.10	-0.08	0.02	0.01
	(0.39)	(0.06)	(24.87)	(0.27)	(0.07)	(0.06)	(0.07)	(0.06)
	{0.128}	{0.356}	{0.903}	{0.674}	{0.137}	{0.192}	{0.723}	{0.881}
Observations	1,826	1,814	1,583	1,833	1,834	1,829	1,832	1,834
Mean (non-eligible)	11.36	0.58	178.13	5.11	0.61	0.63	0.40	0.73
Mean (eligible)	11.39	0.60	159.04	5.11	0.61	0.59	0.41	0.71
Panel B: Males								
Above threshold	-0.25	0.04	-79.69	-0.17	-0.02	-0.02	-0.01	-0.02
	(0.37)	(0.06)	(24.10)	(0.25)	(0.04)	(0.05)	(0.06)	(0.05)
	{0.496}	{0.488}	{0.001}	{0.482}	{0.599}	{0.616}	{0.853}	{0.671}
Observations	2,155	2,149	1,960	2,162	2,162	2,160	2,161	2,162
Mean (non-eligible)	11.75	0.42	226.57	5.03	0.88	0.76	0.46	0.70
Mean (eligible)	11.56	0.43	222.48	4.85	0.87	0.74	0.44	0.69

Data source: Phone Survey Data with RD sample (a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000). Notes: Sampling weights applied. Controls include region (survey data), gender (KYC admin data), and an indicator for whether the respondent was automatically enrolled in mobile money upon SIM card registration (KYC admin data). Missing values for covariates are replaced by 0 and indicated by a dummy. Monetary outcomes are reported in USD and winsorized at 5%. Standard errors in parentheses, p-values in curly brackets.

Table A3: RCT: Balance on Administrative Variables for Full Sample, and Survey Attrition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Balance on Baseline Admin Variables (Full Sample)						Attrition
	Age (KYC)	Urban (KYC)	Total Cash Out	Total Cash In	P2P Transfers Sent	P2P Transfers Received	Could Not Be Surveyed
Panel A: Females							
Finlit	0.039	0.000	-0.192	3.702	-5.501	-3.780	-0.017
	(0.124)	(0.000)	(6.615)	(9.716)	(6.849)	(3.581)	(0.028)
	{0.753}	{0.869}	{0.977}	{0.703}	{0.422}	{0.291}	{0.552}
Salience	0.084	0.000	7.681	7.884	-0.243	0.353	0.019
	(0.124)	(0.000)	(6.985)	(9.881)	(7.136)	(3.683)	(0.029)
	{0.501}	{0.812}	{0.271}	{0.425}	{0.973}	{0.924}	{0.519}
InfoSMS	0.214	0.000	4.155	-6.145	-0.556	1.530	-0.006
	(0.124)	(0.000)	(6.707)	(9.340)	(6.925)	(3.653)	(0.032)
	{0.083}	{0.800}	{0.536}	{0.511}	{0.936}	{0.675}	{0.852}
Observations	8,600	8,611	8,613	8,613	8,613	8,613	2,018
Mean of Control	32.486	0.645	210.848	245.154	170.706	90.524	0.249
Panel B: Males							
Finlit	-0.045	-0.000	0.801	-5.782	-1.265	0.203	-0.035
	(0.099)	(0.000)	(7.303)	(10.485)	(7.622)	(3.591)	(0.027)
	{0.647}	{0.961}	{0.913}	{0.581}	{0.868}	{0.955}	{0.203}
Salience	-0.218	-0.000	4.380	7.689	7.503	4.288	-0.020
	(0.099)	(0.000)	(7.455)	(10.811)	(7.669)	(3.624)	(0.028)
	{0.027}	{0.969}	{0.557}	{0.477}	{0.328}	{0.237}	{0.473}
InfoSMS	-0.015	0.000	-7.397	1.753	0.585	-1.761	0.027
	(0.100)	(0.000)	(7.225)	(10.648)	(7.511)	(3.499)	(0.032)
	{0.883}	{0.991}	{0.306}	{0.869}	{0.938}	{0.615}	{0.397}
Observations	15,510	15,519	15,526	15,526	15,526	15,526	2,217
Mean of Control	35.913	0.548	270.295	385.298	247.608	101.016	0.271

Data source: Administrative KYC and Mobile Money data provided by Airtel. Unit of observation: individual user. Notes: Sample includes all Airtel customers eligible for Kutchova as of the July 2019 relaunch. In column 7, the sample is restricted to users selected for the RCT survey sample. All regressions control for the stratification variables listed in Table 7 notes. The monetary amounts are reported in USD and winsorized at 1%. Robust standard errors in parentheses, p-values in curly brackets. P2P stands for peer-to-peer.

Table A4: RCT: Balance on Survey Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Years of Education	Self-Employed	Monthly Income	HH Size	HH Head	Married	Owns House	Has Electricity
Panel A: Females								
Finlit	-0.032	-0.002	-0.626	0.147	0.000	0.004	0.086	-0.015
	(0.234)	(0.040)	(19.842)	(0.165)	(0.040)	(0.040)	(0.040)	(0.032)
	{0.891}	{0.963}	{0.975}	{0.373}	{0.996}	{0.916}	{0.030}	{0.640}
Salience	-0.158	-0.009	-7.521	0.180	-0.057	0.008	0.017	-0.025
	(0.231)	(0.041)	(21.017)	(0.170)	(0.041)	(0.041)	(0.040)	(0.033)
	{0.495}	{0.820}	{0.721}	{0.288}	{0.169}	{0.848}	{0.668}	{0.450}
InfoSMS	0.044	-0.018	11.463	0.298	-0.029	-0.032	0.091	-0.030
	(0.256)	(0.046)	(22.859)	(0.250)	(0.047)	(0.047)	(0.047)	(0.037)
	{0.862}	{0.694}	{0.616}	{0.235}	{0.531}	{0.494}	{0.054}	{0.416}
Observations	1,510	1,468	1,358	1,512	1,517	1,512	1,507	1,512
Mean of Control	12.111	0.654	196.625	4.841	0.588	0.591	0.326	0.808
Panel B: Males								
Finlit	0.211	0.013	33.563	-0.356	-0.008	-0.016	-0.023	0.046
	(0.240)	(0.037)	(21.097)	(0.160)	(0.023)	(0.030)	(0.036)	(0.032)
	{0.379}	{0.723}	{0.112}	{0.026}	{0.734}	{0.587}	{0.520}	{0.158}
Salience	0.068	0.029	6.495	-0.345	0.004	-0.012	-0.089	0.030
	(0.240)	(0.037)	(20.633)	(0.161)	(0.022)	(0.029)	(0.036)	(0.033)
	{0.776}	{0.436}	{0.753}	{0.032}	{0.855}	{0.681}	{0.013}	{0.354}
InfoSMS	0.218	-0.019	28.617	-0.200	0.023	-0.014	-0.005	0.054
	(0.273)	(0.042)	(24.685)	(0.184)	(0.024)	(0.034)	(0.042)	(0.037)
	{0.423}	{0.657}	{0.246}	{0.276}	{0.343}	{0.681}	{0.906}	{0.149}
Observations	1,796	1,738	1,649	1,803	1,804	1,801	1,798	1,802
Mean of Control	11.729	0.485	283.634	5.240	0.890	0.785	0.493	0.692

Data source: Phone survey data conducted in October 2019 with RCT survey sample (a subset of mobile money users eligible for Kutchova as of the July 2019 relaunch). Unit of observation: individual user. Notes: Sampling weights applied. All regressions control for the relaunch batch to which the user was assigned (N1, N2, E1, or E2), region (survey data), gender (KYC admin data), and whether the respondent was automatically enrolled in mobile money upon SIM card registration (KYC admin data). Monetary outcomes are reported in USD and winsorized at 5%. Robust standard errors in parentheses, p-values in curly brackets.

Table A5: RCT Analysis: Sentiment Towards Kutchova Product (if Ever Borrowed)

	(1) Ever Regretted Taking out Kutchova Loan	(2) Likes Kutchova Product	(3) Dislikes: Tempted to Take Unnecessary loan	(4) Dislikes: Interest Rate Higher than Other Options	(5) Would Use Kutchova Loan for 1,000MWK Emergency	(6) Would Use Kutchova Loan for 3,000MWK Emergency
Finlit	-0.038	0.037	0.027	-0.022	0.046	0.029
	(0.028)	(0.030)	(0.028)	(0.028)	(0.015)	(0.011)
	{0.184}	{0.219}	{0.335}	{0.443}	{0.003}	{0.011}
Salience	0.004	0.009	0.014	-0.007	-0.005	0.007
	(0.031)	(0.031)	(0.028)	(0.029)	(0.014)	(0.010)
	{0.911}	{0.785}	{0.623}	{0.809}	{0.747}	{0.455}
InfoSMS	-0.091	0.095	0.018	-0.011	-0.006	0.008
	(0.031)	(0.031)	(0.035)	(0.035)	(0.017)	(0.013)
	{0.004}	{0.002}	{0.610}	{0.764}	{0.722}	{0.543}
Observations	1,182	1,187	1,190	1,190	3,321	3,321
Mean of Control	.133	.865	.093	.115	.07	.03
P-val Finlit=Salience	0.089	0.239	0.569	0.523	<0.001	0.046
P-val Finlit=InfoSMS	0.029	0.013	0.785	0.719	0.001	0.101

Data source: Phone survey data conducted in October 2019 with RCT survey sample (a subset of mobile money users eligible for Kutchova as of the July 2019 relaunch). Unit of observation: individual user. Notes: Sampling weights applied. See Table 7 notes for list of controls included. Robust standard errors in parentheses, p-values in curly brackets.

Appendix B: Results by Gender

Table B1: RD Analysis: Take-up of Digital Credit

	(1)	(2)	(3)	(4)	(5)	(6)
	Borrowed from Kutchova			Amount borrowed (USD)		
	Full Sample	Survey Sample		Full Sample	Survey Sample	
	Since July 2019	Since July 2019	In 3 Months Prior to Survey	Since July 2019	Since July 2019	In 3 Months Prior to Survey
Panel A: Females						
Above credit eligibility threshold	0.37	0.40	0.17	1.63	1.92	0.50
	(0.04)	(0.05)	(0.04)	(0.27)	(0.39)	(0.13)
	{<0.001}	{<0.001}	{<0.001}	{<0.001}	{<0.001}	{<0.001}
Observations	4,187	1,860	1,860	4,187	1,860	1,860
Mean (non-eligible)	0.0020	0.0030	0.0020	0.0120	0.0200	0.0080
Mean (eligible)	0.37	0.40	0.15	2.18	2.33	0.63
Panel B: Males						
Above credit eligibility threshold	0.32	0.33	0.10	1.85	2.30	0.49
	(0.03)	(0.04)	(0.03)	(0.24)	(0.40)	(0.13)
	{<0.001}	{<0.001}	{<0.001}	{<0.001}	{<0.001}	{<0.001}
P-value Females=Males	0.325	0.275	0.121	0.555	0.504	0.981
Observations	6,473	2,122	2,122	6,473	2,122	2,122
Mean (non-eligible)	0.0020	0.0040	0.0020	0.0150	0.0210	0.0070
Mean (eligible)	0.36	0.42	0.11	2.15	2.59	0.62

Data source: Administrative data for mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000 (excluding groups N3 and N4). Notes: This table presents the same analysis as Table 3 but reports results separately by gender. See Table 3 for information on the Stata command, controls, and running variable used. Analysis in columns 2, 3, 5 and 6 is restricted to the sample who completed the survey, and sampling weights are applied. Monetary outcomes are reported in USD and winsorized at 1%. "P-value Females=Males" is the p-value of a two-tailed Z-test testing whether the "Above credit eligibility threshold" coefficient is equal for females and males. Standard errors in parentheses, p-values in curly brackets.

Table B2: RD Analysis: Usage of Credit Across All Sources (Past 3 Months)

	(1)	(2)	(3)	(4)	(5)	(6)
	=1 if took		Number of loans			Total Amount
	Kutchova	Any Loan	Digital Airtime	Friends / Family	VSLA / ROSCA	Borrowed (USD)
Panel A: Females						
Above credit eligibility threshold	0.13	0.19	-0.39	0.29	0.02	2.22
	(0.05)	(0.08)	(1.48)	(0.21)	(0.11)	(10.45)
	{0.004}	{0.027}	{0.793}	{0.158}	{0.887}	{0.832}
Observations	1,285	1,270	1,147	1,285	1,288	1,270
Mean (non-eligible)	0.01	0.62	4.96	0.37	0.28	31.71
Mean (eligible)	0.16	0.72	5.16	0.35	0.29	31.39
Panel B: Males						
Above credit eligibility threshold	0.11	0.13	2.23	0.11	0.03	5.74
	(0.04)	(0.07)	(1.20)	(0.15)	(0.05)	(7.60)
	{0.009}	{0.066}	{0.064}	{0.457}	{0.599}	{0.450}
P-value Females=Males	0.651	0.588	0.170	0.493	0.911	0.785
Observations	1,606	1,585	1,440	1,606	1,608	1,585
Mean (non-eligible)	0.0170	0.5630	4.0860	0.5150	0.0820	28.8120
Mean (eligible)	0.16	0.70	5.28	0.47	0.09	29.77

Data Source: Phone Survey Data with RD sample (a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000). Notes: Sample limited to those administered version 2 (=RD) of the survey since version 1 did not include information on past three months (only last loan). This table presents the same analysis as Table 4 but reports results separately by gender. See Table 4 for information on the Stata command, controls, and running variable used. Sampling weights applied. Monetary outcomes reported in USD and winsorized at 5%. "Total amount borrowed" include all borrowing in the past 3 months but excludes very uncommon sources such as moneylenders and MFIs. "P-value Females=Males" is the p-value of a two-tailed Z-test testing whether the "Above credit eligibility threshold" coefficient is equal for females and males. Standard errors in parentheses, p-values in curly brackets.

Table B3: RD Analysis: Financial Security

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Financial Security (higher value is higher well-being)						
	=1 if satisfied with financial well-being	Degree of Preparation for Future Emergencies (in SD)	Index of Ability to Pay for Non-food Expenses (in SD)	Food Security Index (in SD)	Used Digital Loan to Cope with Shock	Total Savings (USD)	Liquid Savings (USD)
Panel A: Females							
Above credit eligibility threshold	0.17	0.02	0.19	0.19	0.00	11.68	-11.51
	(0.06)	(0.12)	(0.13)	(0.14)	(0.00)	(19.01)	(16.01)
	{0.005}	{0.871}	{0.132}	{0.177}	{0.454}	{0.539}	{0.472}
Observations	1,834	1,834	1,834	1,825	1,324	1,511	1,833
Mean (non-eligible)	0.54	-0.07	-0.02	-0.07	0.00	84.31	76.03
Mean (eligible)	0.59	0.07	0.08	-0.08	0.00	94.95	82.14
Panel B: Males							
Above credit eligibility threshold	0.10	0.11	0.00	-0.12	-0.00	6.31	-16.19
	(0.05)	(0.11)	(0.10)	(0.11)	(0.00)	(21.78)	(14.86)
	{0.064}	{0.313}	{0.985}	{0.270}	{0.408}	{0.772}	{0.276}
P-value Females=Males	0.363	0.576	0.247	0.082	0.343	0.853	0.831
Observations	2,162	2,162	2,161	2,155	1,485	1,797	2,160
Mean (non-eligible)	0.5570	0.0460	0.0200	0.0270	0.0010	128.3920	85.5250
Mean (eligible)	0.61	0.17	0.21	0.12	0.00	144.18	82.97

Data Source: Phone Survey Data with RD sample (a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000). Notes: Sample limited to those administered version 2 (=RD) of the survey since version 1 did not include information on past three months (only last loan). This table presents the same analysis as Table 5 but reports results separately by gender. See Table 5 for information on the Stata command, controls, and running variable used. Sampling weights applied. Index of ability to pay for non-food expenses is derived from 4 variables: payments for health expenditures, bill payments, school fees and ability to help family/friends in time of need. Food security index is derived form 4 variables: relying on less expensive foods, limiting meal sizes, reducing number of meals and borrowing food. We compute indices using weighted averages and standardizing against the non-eligible group. "Total Savings" is the value reported by the respondent when asked: "How much money did you have in savings (across all your saving places) at the end of last month?" "Liquid Savings" sums up reported savings across 5 saving methods (saving box, bank, mobile money, MFI/SACCO, VSLA). Monetary amounts are reported in USD and winsorized at 5%. "P-value Females=Males" is the p-value of a two-tailed Z-test testing whether the "Above credit eligibility threshold" coefficient is equal for females and males. Standard errors in parentheses, p-values in curly brackets.

Table B4: RCT Analysis: Summary of Results by Gender and with Strata Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Knowledge		Borrowing		Repayment		Satisfaction	
	Knows Fee/ Interest Rate on Kutchova Loans	Knows After How Many Days Loan is Due	Kutchova Amount borrowed 0-3 Months	Kutchova Amount borrowed 3-9 Months	Repayment: Ever Late	Total Late Fees Paid	Would Use Kutchova Loan for MWK1000 Emergency	Ever Regretted Taking out Kutchova Loan
Panel A: Females								
Finlit	0.171	0.194	0.454	0.634	0.003	-0.022	0.041	-0.064
	(0.039)	(0.040)	(0.115)	(0.275)	(0.011)	(0.100)	(0.024)	(0.052)
	{<0.001}	{<0.001}	{<0.001}	{0.021}	{0.811}	{0.830}	{0.083}	{0.219}
Salience	0.041	0.081	0.137	0.437	0.012	-0.028	0.005	-0.030
	(0.039)	(0.041)	(0.113)	(0.277)	(0.010)	(0.098)	(0.022)	(0.055)
	{0.298}	{0.045}	{0.225}	{0.114}	{0.250}	{0.776}	{0.835}	{0.591}
InfoSMS	0.038	0.030	0.049	-0.068	0.013	0.013	-0.005	-0.115
	(0.047)	(0.046)	(0.118)	(0.282)	(0.012)	(0.112)	(0.026)	(0.052)
	{0.419}	{0.511}	{0.678}	{0.811}	{0.266}	{0.907}	{0.856}	{0.027}
Observations	1,511	1,512	8,613	8,613	3,141	1,540	1,517	545
Mean of Control	.278	.329	1.667	3.063	.954	2.169	.071	.104
P-val Finlit=Salience	<0.001	0.001	0.008	0.496	0.342	0.947	0.045	0.395
P-val Finlit=InfoSMS	0.003	<0.001	0.001	0.017	0.347	0.749	0.059	0.220
Panel B: Males								
Finlit	0.179	0.122	0.190	0.138	-0.002	0.014	0.041	-0.017
	(0.036)	(0.034)	(0.109)	(0.272)	(0.009)	(0.088)	(0.021)	(0.048)
	{<0.001}	{<0.001}	{0.082}	{0.612}	{0.844}	{0.876}	{0.051}	{0.727}
Salience	0.049	0.036	0.033	-0.074	-0.009	-0.009	-0.003	0.018
	(0.035)	(0.034)	(0.105)	(0.267)	(0.009)	(0.091)	(0.020)	(0.047)
	{0.155}	{0.285}	{0.757}	{0.781}	{0.339}	{0.923}	{0.890}	{0.696}
InfoSMS	0.047	0.028	0.161	0.127	0.003	0.097	-0.003	-0.087
	(0.044)	(0.042)	(0.117)	(0.295)	(0.009)	(0.101)	(0.023)	(0.053)
	{0.286}	{0.498}	{0.169}	{0.668}	{0.763}	{0.334}	{0.882}	{0.105}
Observations	1,793	1,795	15,526	15,526	5,899	3,003	1,804	637
Mean of Control	.305	.367	2.206	4.642	.936	2.837	.07	.146
P-val Finlit=Salience	<0.001	0.005	0.148	0.434	0.420	0.792	0.020	0.378
P-val Finlit=InfoSMS	0.002	0.018	0.815	0.970	0.615	0.393	0.046	0.136
P-val Finlit Female=Finlit Male	0.725	0.306	0.093	0.338	0.687	0.882	0.755	0.725

Data source: Phone survey data conducted in October 2019 (columns 1-2 and 7-8) and Kutchova administrative data (columns 3 to 6). Unit of observation: individual user. Notes: Sample includes Airtel customers eligible for Kutchova as of the July 2019 relaunch. In Columns 1-2 and 7-8, the sample is further restricted to the subset of customers who completed the RCT survey, sampling weights are applied, and regressions include control listed in Table 7 notes. In columns 3 to 6, regression include controls listed in Table 10 notes. All regressions include randomization strata fixed effects. Monetary outcomes are reported in USD and winsorized at 1%. Robust standard errors in parentheses, p-values in curly brackets.

Appendix C: RCT Intervention details

We present below the scripts for the IVR modules (Finlit and Salience) described in the main text. These were interactive modules that could be completed from any type of cell phone. Respondents were asked to key in answers by pressing e.g. "1" for yes, "2" for no.

Figure C1: Finlit Intervention: IVR Script

Block Label		Skip Logic	incentive threshold
intro	This is an interactive learning tool designed to teach about Airtel Money and improving your finances. If you complete the quiz, you will receive 500K talk time. If you get disconnected, you can call back at [insert phone number here].		No
Q1	1. Let's begin. This is a story about Mary; Mary owns a small grocery store. Mary's business has been doing well lately; in fact, she's almost sold everything in her store! Mary realizes that she needs to purchase more inventory. She must do this soon, or she will not have anything left in her store. Re-stocking inventory, however, is expensive - it will cost 10,000 MWK. Although Mary's shop has been doing well, she does not have this money in savings. If Mary wants to re-stock her store, she'll need to borrow money. Mary calls her sister to ask if she can borrow money. Mary's sister can loan Mary the money, but not until next week. This is a problem because Mary's store is almost empty; she needs the money now. Mary hears on Airtel's radio show that Airtel has begun offering Kutchova loans again. Mary tries to remember details of the Kutchova loan. Do you know if there is a fee for taking a Kutchova loan? [KNOWLEDGE: FEE] If there is a fee to take out a Kutchova loan, press 1 If there is no fee to take out a Kutchova loan, press 2 If you'd like to hear the question again, press 0		No
Q1.1	That is correct. There is a fee to take out a Kutchova loan.		No
Q1.2	Not quite. There is a fee to take out a Kutchova loan.		No
Q2	Do you know how much the fee would be if Mary took out a Kutchova loan? If she would have to pay 10% of the loan amount, press 1 If she would have to pay 5% of the loan amount, press 2 If you'd like to hear the question again, press 0		No
Q2.1	Correct! The fee for a Kutchova loan is 10% of the loan amount. For example, if Mary borrows 10,000 MK, the fee would be 1,000.		No
Q2.2	Not quite. The fee for a Kutchova loan is 10% of the loan amount. For example, if Mary borrows 10,000 MK, the fee would be 1,000.		No
Q3	Mary considers taking a Kutchova loan to pay for the inventory, but she doesn't know when she'll be able to pay back the loan. What will happen if 7 days pass and Mary still has not paid back the loan? [KNOWLEDGE: REPAYMENT PERIOD] If Airtel will forget about Mary; she will never have to pay back the loan, press 1. If police will come and take the money from Mary, press 2 If after 7 days, Mary's loan will be considered late and she will need to repay soon to avoid late fees, press 3 If you'd like to hear the question again, press 0		No
Q3.1	Not quite. Kutchova will not forget about Mary's loan. The loan is due after 7 days. After 7 days, Mary's loan will be considered late and she will need to repay soon to avoid late fees.		No

Figure C1: Finlit Intervention: IVR Script (continued)

Block Label		Skip Logic	incentive threshold
Q3.2	Not quite. The loan is due after 7 days. After 7 days, Mary's loan will be considered late and she will need to repay soon to avoid late fees		No
Q3.3	That's correct! After 7 days, Mary's loan will be considered late and she will need to repay soon to avoid late fees.		No
Q4	Now, back to Mary's sister, who said she could loan Mary the money next week. Mary thinks to herself, "I will take a Kutchova loan now and then use my sister's money to pay back the Kutchova loan next week." But what if Mary's sister is delayed, and Mary doesn't make many sales next week? What will happen if Mary takes out a Kutchova loan and it takes her more than 15 days to pay back the loan? [KNOWLEDGE: PENALTY] If nothing will happen; there is no late fee, press 1 if Mary will be charged a late fee, press 2 if Mary's sister will be charged a late fee, press 3 If you'd like to hear the question again, press 0		No
Q4.1	Actually, there is a late fee. The late fee is 2.5% of the outstanding balance. So, if Mary owes 10,000 then she will be charged 250k every 15 days. Mary will be charged this fee three times if she fails to repay.	If user provides this answer, proceed to Q6	No
Q4.2	Correct! The late fee is 2.5% of the outstanding balance. So, if Mary owes 10,000 then she will be charged 250k every 15 days. Mary will be charged this fee three times if she fails to repay.	If user provides this answer, proceed to Q5	No
Q4.3	Not quite. If Mary cannot repay the loan in 15 days, she is responsible for paying a late fee. So, if Mary owes 10,000 then she will be charged 250k every 15 days. Mary will be charged this fee three times if she fails to repay.	If user provides this answer, proceed to Q6	No
Q5	Mary needs the money urgently, otherwise her store will be empty next week and she will not earn money she needs to feed her family. Before Mary takes a loan, she wants to find out more information about this loan. Which of these are good ways to get information about Kutchova? If Mary should speak to an Airtel agent, press 1 If Mary should listen to Airtel's radio show on Zodiak Radio, press 2 If Mary should ask her sister, press 3 If you'd like to hear the question again, press 0		No
Q5.1	Correct. However, Airtel's agents might not know the fees and conditions of the Kutchova loan. In addition, Mary should listen to Airtel's radio show on Zodiak Radio. Airtel's show is currently on every Wednesday at 5.05pm, but the time might change, so be sure to listen to Zodiak to catch the Airtel show.		No
Q5.2	Correct! Mary should listen to Airtel's radio show on Zodiak Radio. Airtel's show is currently on every Wednesday at 5.05pm, but the time might change, so be sure to listen to Zodiak to catch the Airtel show.		No
Q5.3	Not quite. Mary's sister might not know the fees and conditions of the Kutchova loan. Instead, Mary should listen to Airtel's radio show on Zodiak Radio. Airtel's show is currently on every Wednesday at 5.05pm, but the time might change, so be sure to listen to Zodiak to catch the Airtel show.		No

Figure C1: Finlit Intervention: IVR Script (continued)

Block Label		Skip Logic	incentive threshold
Q6	In the end, Mary takes a Kutchova loan for 10,000 MWK. Then, Mary receives an SMS that her parents have sent her 1,000 MWK via Airtel Money. With the money from her parents and the Kutchova loan, her total Airtel Money balance is now 11,000 MWK. Mary gets in line at the Airtel Money agent and cashes out 10,000 MWK to buy new inventory for the grocery store. How much money is left in Mary's Airtel Money account? Remember, Mary's balance was 11,000 MKW when she withdrew 10,000. If Mary has 1,000 MKW left in her Airtel Money account press 1 If Mary has 620 MWK left in her Airtel Money account, press 2 If you'd like to hear the question again, press 0		No
Q6.1	Not quite. Mary checks her balance and sees that only 620 MWK is left in her account; this is because the cash out fee for 10,000 MWK was 380 MWK. Mary is lucky her parents sent her money because, if not, she would not have been able to withdraw the 10,000 MWK she needed to pay for inventory. To learn more about cashout fees, speak to a nearest Airtel agent.		No
Q6.1	Correct! Mary's balance is 620 MWK; this is because the cash out fee for 10,000 MWK was 380 MWK. Mary is lucky her parents sent her the money because, if not, she would not have been able to withdraw the 10,000 MWK she needed to pay for the		No
Q7	Mary has purchased her inventory. Now it is late at night and Mary wants to call her parents to thank them. Mary also wants to call her children at home to tell them she'll be home soon. Mary also wants to call her sister to say that she took out the Kutchova loan. In short, Mary wants to call many people, but, unfortunately, she is out of airtime. Mary can borrow airtime with Kutapa. Do you know if there is a fee for taking a Kutapa loan? If the fee is 10% of the loan amount, press 1 If there is no fee for taking a Kutapa loan, press 2 If the fee is 100% of the loan amount, press 3 If you'd like to hear the question again, press 0		No
Q7.1	Correct! The fee for a Kutapa loan is 10% of the loan amount. For example, if Mary borrows 1,000 MK of airtime, the fee would be 100.		No
Q7.2	Not quite. The fee for a Kutapa loan is 10% of the loan amount. For example, if Mary borrows 1,000 MK of airtime, the fee would be 100.		No
Q7.3	Not quite. The fee for a Kutapa loan is 10% of the loan amount. For example, if Mary borrows 10,000 MK of airtime, the fee would be 100.		No
Q8	How much airtime would you borrow if YOU were Mary? If I were Mary, I would borrow 200 MK and pay 20 extra. I would only call my children to say that I'm on my way home, and wait until tomorrow to purchase more airtime, press 1 If I were Mary, I would borrow 1000 MK and pay 100 extra. I would call my children, but also call my parents to thank them immediately, press 2 I don't like running out of airtime, so, if I were Mary, I would borrow 2000 MK and pay 200 extra. I would make as many calls as I want, press 3 If you'd like to hear the question again, press 0		No
Q8.1	Mary thinks like you and borrows 200 MK of airtime. She makes one call to her children to tell them she will be home soon.		No
Q8.2	Mary thinks like you and borrows 1000 MK of airtime. She calls her children and her parents.		No

Figure C1: Finlit Intervention: IVR Script (continued)

Block Label		Skip Logic	incentive threshold
Q8.3	Mary thinks like you and borrows 2000 MK. She calls her children, her parents, and her sister, and has a long chat with everyone. After making these calls, Mary still has airtime leftover.		No
Q9	Mary makes it home and goes to bed. She wakes up the next morning and thinks about how convenient Kutapa was because, late at night, it would be hard to top up airtime. Mary knows it is best not to borrow airtime carelessly...Think about how much airtime a person can borrow in a year, and how much it would cost. Select one of these three options to find out the yearly costs - If you want to find out the yearly costs if you borrowed 500 MK every week, press 1 If you want to find out the yearly costs if you borrowed 1000 MK every week press 2 If you want to find out the yearly costs if you borrowed 2000 MK every week press 3 If you'd like to hear the question again, press 0		No
Q9.1	Kutapa is convenient. But, if you borrow 500 MK every week, you pay the extra 10% fee every time! If you add it up over a year, this would cost 2,400 MK or more.		No
Q9.2	Kutapa is convenient. But, if you borrow 1000 MK every week, you pay the extra 10% fee every time! If you add it up over a year, this would cost 4,800 MK or more.		No
Q9.3	Kutapa is convenient. But, if you borrow 2000 MK every week, you pay the extra 10% fee every time! If you add it up over a year, this would be 9,600 MK or more.		No
Q10	A week passes and Mary's sister is able to loan Mary money, as promised. So, Mary pays back the Kutchova loan using the money from her sister and does not incur a late fee. Mary wonders what would have happened if she had never repayed her loan. If Mary could have been reported to a credit bureau, press 1 If nothing bad could have happened, press 2 If you'd like to hear the question again, press 0		No
Q10.1	That's correct! If Mary had never repaid the loan, her name could have been reported to a credit bureau, which is an agency responsible for tracking people who don't pay their debts. If you are reported to a credit bureau, this can prevent you from taking loans in the future. This includes loans from Airtel, but also from microfinance institutions and banks.		No
Q10.2	Not quite. If Mary had never repaid the loan, her name could have been reported to a credit bureau, which is an agency responsible for tracking people who don't pay their debts. If you are reported to a credit bureau, this can prevent you from taking loans in the future. This includes loans from Airtel, but also from microfinance institutions and banks.		No
	Fortunately, Mary managed to pay off all her debt. Now Mary's business is running smoothly, with the shelves full of inventory. Mary has agreed to pay back her sister in small amounts over the upcoming months. Mary thinks about what she has learned...		No
Q11	First, when borrowing, it is important to know the terms of loans, so you are not surprised by late fees or penalties.		yes

Figure C1: Finlit Intervention: IVR Script (continued)

Block Label		Skip Logic	incentive threshold
Q11.1	Second, it is important to know the costs of taking a loan. For example, even though borrowing airtime can be convenient, the costs of repeatedly taking loans will add up over time.		yes
Q11.2	Third, there are many costs associated with borrowing money. There are costs directly associated with the loan, like penalties for late repayment, but there are also unexpected costs such as withdrawal fees. By borrowing only when you need to, you can save more. With more savings, you will need to borrow less in the future (and avoid more fees!).		yes
Q11.3	Correct!		yes
Q12	Thank you for playing. Please be informed that Kutchova is back and the terms and conditions are the same as before, but soon Airtel will start offering new loan products with different terms and conditions, so if you plan to take a loan, be sure to know the terms and fees before you take the loan! Next time you need cash rapidly, what would be your preferred source for this cash? If you would borrow from relatives or friends press 1 If you would borrow from ROSCA press 2 If you would borrow through KUTCHOVA loan press 3 If you would borrowfrom a local moneylender press 4 if other, press 5"		yes
end	We hope you enjoyed learning about Kutchova loans and responsible borrowing. Have a good day!		yes

Figure C2: Salience Intervention: IVR Script

Block Label		Incentive threshold
intro	This is an interactive learning tool designed to teach about Airtel Money. If you complete the quiz, you will receive 500K talk time. If you get disconnected, you can call back at XXXXXXXXX.	No
Q1	Let's begin. This is a story about Mary; Mary owns a small grocery store. One day, a customer enters Mary's store and asks if he can pay for groceries using Airtel Money. Mary isn't familiar with Airtel's services so she does not know how to answer. Which is the correct answer? 1 – If the customer can transfer money from their Airtel Money account to Mary's Airtel Money account, press 1 2 – If it is impossible for one Airtel Money user to transfer funds to another Airtel Money user, press 2 If you'd like to hear the question again, press "XX"	No
Q1.1	That's correct!	No
Q1.2	Not quite. It is possible for the customer to transfer money from their Airtel Money account to Mary's account.	No
Q2	Now Mary feels curious - what other products and services does Airtel offer? 1 – If Airtel offers a product called Kupatsa, press 1 2 – If Airtel offers a product called Kutchova, press 2 If you'd like to hear the question again, press "XX"	No
Q2.1	Not quite, Airtel does not have any product or service called Kupatsa. Airtel does, however, have a product called Kutchova; Kutchova is an instant loan that can be obtained through the phone for people with a long enough history of Airtel money usage.	No
Q2.2	That's correct! Airtel does have a product called Kutchova. Kutchova is an instant loan that can be obtained through the phone for people with a long enough history of Airtel money usage.	No
Q3	Mary agrees to sell groceries to the customer and receive payment to her Airtel Money account. Now, if any customer comes in asking about Airtel products or services, Mary will be prepared with the answers thanks to your help. We hope you enjoyed this short quiz about Airtel Money. Have a good day!	Yes

Script encouraging subscribers to activate IVR module

- This is IPA, an NGO in Lilongwe. Take a quiz about Airtel's Kutchova loans. Complete the quiz to receive 500k talk time in the next few days. Flash 0990024120!

Information SMS

- Airtel Kutapa terms & conditions: For a loan of K1000, the interest is 100, so you automatically repay K1100 the next time you top up.
- Airtel Kutchova terms & conditions: For a loan of K1000, the interest is 100, so you must repay K1100 in 7 days to avoid late fees.
- Airtel Kutchova terms & conditions: A penalty of 2.5% of your outstanding Kutchova loan balance is added to your debt every 15 days.