Is Digital Credit Filling a Hole or Digging a Hole? Evidence from Malawi*

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May 20, 2023

Abstract

Digital credit has expanded rapidly in Africa, with opaque loan terms amidst low consumer financial literacy. Rich data from Malawi shows substantial demand for a digital loan with a base interest rate of 10% over 15 days, yet most borrowers are not aware of loan terms, repay late and incur substantial late fees. Regression discontinuity analyses show no evidence that access to small digital loans harms consumers' perceived well-being. A short, randomized, phone-based financial literacy intervention improved knowledge but did not increase timely loan repayment, and modestly *increased* loan demand, ultimately increasing the likelihood of ever defaulting.

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

*The authors are from ID Insight (Brailovskaya); Stanford, CEGA, CEPR, J-PAL, and NBER (Dupas); and UC Santa Cruz, CEGA, J-PAL, and NBER (Robinson). We gratefully acknowledge research support from the CEGA Digital Credit Observatory (funded by the Bill and Melinda Gates Foundation). These funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. We thank Airtel Malawi for their cooperation, especially Tione Kafumba, Bigboy Makaloma, and Chris Sukasuka. The research protocol was approved by the Malawi National Committee on Research in the Social Sciences and Humanities (NCRSH) and by the UCSC IRB. The experimental component is registered in the AEA RCT registry (AEARCTR-0004139). We thank IPA Malawi, and especially Patrick Baxter, Minsu O, Rachel Schwartz, and Monica Shandal for project management. We are especially grateful to Esau Banda and Patrick Simbewe for their assistance both at IPA and even after the data collection had ended. We are grateful to Camille Falezan and Isoke Nelson for research assistance. We thank Eilin Francis for her collaboration at early stages of the project. We thank Berk Özler, Djibrilla Adamou Issa and Tavneet Suri for helpful discussions, and seminar participants at a CEGA DCO webinar, the 2021 ASSA meetings, HKUST, USC, IFPRI and the World Bank Africa Region for helpful comments.

1 Introduction

Digital credit has exploded in popularity across the world in recent years. In Africa, digital lending now outpaces traditional lending in early adopter countries like Kenya, and tens of millions of loans are being transacted annually.[1] 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.

The most common form of digital credit currently offered in Africa is 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).

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 (potentially 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 effects of digital credit as currently offered in Africa. To fill this gap, we combine a rich set of administrative and survey data from Malawi around the launch of a new digital credit product to (1) document suggestive evidence of suboptimal repayment behavior; (2) examine impacts of access to digital credit on borrower outcomes; and (3) evaluate a low-touch, low-cost financial literacy intervention.

[1] See Ogada and Hammond (2021), Francis et al. (2017), and Robinson et al. (2022) 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.

We focus on a digital credit product called *Kutchova* which is offered by the mobile network operator (MNO) Airtel in Malawi. Similar to products in other African countries, *Kutchova* loans are issued by a bank but transacted, on Airtel's mobile money platform. The loans include a 10% facilitation fee and are due in 15 days, and feature sizeable late fees that far exceed those reported by other digital credit providers and that are not transparently disclosed (the late fee reaches up to 22.5% after 30 days). 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, and default or late payment is common: 11% of loans 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.[5]

In 2019-20, *Kutchova* was relaunched after a dormant period and we coordinated with Airtel to conduct two related empirical analyses timed at the relaunch. First, we conduct a regression discontinuity design (RDD) analysis, in which we compare users just above and below the credit score cutoff to qualify for loans. Despite the high interest rate, we find robust demand: 34% of barely-eligible customers 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. Descriptive evidence suggests that in the absence of these loans, most people would not have had access to alternative sources of credit. We find a positive and statistically significant 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 the RDD analysis shows positive, mostly insignificant effects, the widespread phenomenon of paying late and incurring substantial fees suggests the possibility of harm from such loans. In some cases, paying back late seems to clearly be a mistake: in particular, a surprisingly large fraction of borrowers fail to repay despite having funds available on their

[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.

mobile money account; these loans are then automatically repaid on the mobile money platform, but with the late fee added. We hypothesized that lack of information about loan terms and fees was a cause of this behavior. To shed light on this, we designed and implemented a financial literacy "interactive voice response" (IVR) intervention (referred to as "Finlit") 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. Customers were informed of the late fee as stipulated in the Terms and Conditions available at the time, but to the research team's surprise, the actual fee charged was even higher (12.5% instead of 2.5%).[6] The module 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 Finlit intervention to three other groups: a "Salience" 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 ("InfoSMS") which were identical to the ones sent to the Finlit group, and a pure control group.

As expected, the financial literacy ("Finlit") intervention increased knowledge about loan terms (by about 0.32 standard deviations relative to the control group). Less expected, we also find that the intervention modestly *increased* loan demand, both on the extensive and intensive margins. The probability of taking out a loan following 9 months after the intervention increased by 1.9 percentage points (compared to 40.6% in the control group), the total amount borrowed increased by 0.57 USD compared to 6.59 USD in the control group (representing an 8% increase). In fact, at the end of the Finlit module, participants were asked what source of cash they would prefer "next time you need cash rapidly". The overwhelming majority said *Kutchova* (88%). There are several possible explanations for our finding that an intervention that increases awareness of costs and risks only makes the product more attractive. These include that people actually overestimated the costs of credit, which is consistent with the the fact that people were more likely to report wanting the loan afterwards; or behavioral reasons like ambiguity aversion (Bryan 2019). Results are unlikely to be driven by a simple "advertisement" effect, since the Salience intervention had no effect, although it may be possible that the financial literacy message was perceived as a form of "informative advertising" while

[6] We discuss the implications of this issue for the interpretation of the treatment effects at length in section 5.

the salience intervention was perceived as pure "persuasive" advertising.

While we find a positive but insignificant effect on the probability of repaying a specific loan (1.6 percentage points on a base of 41.3%), the Finlit group is significantly more likely (1.6 percentage points on a base of 19.7%) to have defaulted following 9 months after the intervention (because they take out more loans). We do not detect any impacts on these outcomes for Salience or InfoSMS group. Ultimately, the effect of the intervention on borrower welfare is ambiguous and depends in part on the consequences of ultimately defaulting. While Airtel's offical communication with users states that default will be reported to the credit bureau, in private communication Airtel has repeatedly stated that they have not reported anyone to date. At this time, therefore, the consequence of default seem limited to being barred from future *Kutchova* borrowing, and thus it may be rational to default. 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), at least for those users who would otherwise have qualified for formal credit.

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.[7] Our paper also contributes to the literature showing that many consumers are poorly informed about costs of financial services, particularly "shrouded fees" such as late or overdraft fees.[8] A particularly related paper is Alan et al. (2018), which finds that informing customers in Turkey about the presence of an overdraft facility at 60% APR increases the usage of the service. Our results differ in one respect, however, in that we find that explicitly mentioning the cost of credit increases demand, whereas in Alan et al. (2018) marketing did not increase demand if the cost of the overdraft were made salient via a discount promotion. Another closely related study is Bertrand and Morse (2011), which inspired our design, and which finds that providing information about payday loans caused borrowers to reduce their demand.[9] By contrast, in the

[7]There is a larger literature on the effects of short-term, high-interest rate loans more generally. Among others, see papers such as Morse (2011), Zinman (2010) and Melzer (2011) in the US, Angelucci et al. (2015) in Mexico, Karlan and Zinman (2010) in South Africa and Karlan and Zinman (2011) in the Phillipines.

[8]See papers such as Stango and Zinman (2016) and Stango and Zinman (2009) in the US; see Garz et al. 2021 for a recent review of consumer protection in low- and middle-income countries.

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

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 remainder of the paper proceeds as follows. Section 2 provides the background on the digital product considered and describes the data. Section 3 presents motivating evidence on loan demand and repayment behavior. Section 4 presents the RDD analysis estimating impacts on well-being, while Section 5 presents the financial literacy RCT results. Section 6 discusses heterogeneity and Section 7 concludes.

2 Background and Data

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.[10] 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 have 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%.[11] 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 (USD 1.4) withdrawal is 8%).[12] 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 by the due time on the due date, the lender attempts "auto recovery",

between more- and less-informed consumers.

[10] *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.

[11] The annual inflation rate was 8-9% during the time period.

[12] Note, however, that the cash-out fee is not relevant for airtime purchases (about 30% of loans) or for transactions made on the Airtel network. However, using mobile money for transactions was relatively uncommon in Malawi during this time period.

i.e., automatic withdrawal from the borrower's mobile money account. Borrowers are charged the late fee for auto-recovery.

While the facilitation fee of 10% is clearly stated, 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 1 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 immediately *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 in default.

The high late fees we observe far exceed those reported by other digital credit providers,[13] and, as just mentioned, 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 fees were 12.5% then 10% 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 has not started doing this.[14] 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.

[13] See Robinson et al. 2022 for a tabulation of fees on some other digital products.

[14] There are multiple private credit bureaus operating in Malawi such as Credit Data Malawi, CRB Africa, and TransUnion. As of January 2023, Airtel customer service representatives continue to state that they have not yet started actually reporting people, though they do threaten delinquent borrowers with reporting.

2.2 Data

2.2.1 Administrative data from Airtel

We have three 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 as of May 20, 2020, and fees incurred.

2.2.2 Credit Scores from the Scoring Firm

In the July 2019 relaunch, all 590,000 Airtel customers who had not previously borrowed from *Kutchova* but met some criteria were given a "predicted profitability" value.[15] 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.[16] 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.[17] 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.

2.2.3 Survey Data

We conducted a short phone survey in two batches, one in the Fall 2019 ("RCT survey") and one in the Spring 2020 ("RD survey"). Because the surveys were conducted over the phone,

[15] While we do not have access to the credit scoring algorithm, we were in touch with Airtel and the credit scoring firm during the scoring process. Only mobile money users who had an account for at least 6 months were eligible, and it is our understanding that the only data used to generate a score was mobile money usage (to our knowledge, the data was not linked to other databases held by Airtel, such as airtime usage or repayment of digital airtime loans, or to data held by any other firm). We suspect that the scoring firm was predicting the probability of repayment; however, in practice profitability is highest for those who pay back late and incur fees so in the future scoring would presumably take this into account.

[16] 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.

[17] 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 because we expected digital credit to have modest effects on downstream outcomes, we decided not to measure outcomes such as expenditures, income, or labor supply and opted to keep the survey relatively short (the survey ultimately took an average of 25 minutes to adminster). In addition to basic demographic indicators, the survey focused on knowledge, usage, and experience with *Kutchova*, usage of other sources of credit and savings, self-reported financial well-being, and experience with unexpected shocks.

We conducted the RCT survey from late September to late October 2019, three months after the July 1, 2019 relaunch of *Kutchova*. Of the 4,445 respondents we attempted to survey, we successfully completed surveys with 3,321 (75%) of them. Our completion rate is similar to the 69% completion rate in Suri et al. (2021), and much higher than the rate among Kenyan smartphone users in Björkegren et al. (2021).

For the RD survey we conducted upon receiving the shortcode in March 2020, we sampled a random subset of users within the 827 to 842 score range (recall the *Kutchova* eligibility threshold was 834).[18] 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.[19] All our analyses include sampling weights.

The RD survey was implemented over the phone between March 2 and April 8, 2020 (just as the COVID-19 crisis was taking hold).[20] 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 survey and thus were not resurveyed. The October 2019 and March 2020 surveys were nearly identical; other than minor refinements, the main difference is that the 2019 version asked only about the last *Kutchova* loan while the 2020 version asked about all loans over the past 3 months. About 70% of those we attempted to survey for the RD analysis were successfully surveyed, and attrition was balanced above and below the threshold (see Table B1, column 1).

[18] 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).

[19] For men, we sampled all users with scores from 831 to 839, 20% of users with a score of 830 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.

[20] 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. (2022) for more detail on the effect of COVID-related disruptions in Malawi.

2.3 Sample Characteristics

Table 1 presents summary statistics. Columns 1-3 show the universe of mobile money users, while Columns 4-7 show those who qualified for *Kutchova* (i.e, they received a credit score of 834 or above, or were previous Kutchova customers). 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 large 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.[21] 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. *Kutchova* access is very limited: only 1.73% of women and 2.18% of men are eligible (Columns 4-6). Women make up only 36% of the eligible population.

3 Motivating Evidence

This section uses administrative data and survey data to provide some key facts about Kutchova users, patterns of usage, and the broader credit context in which our sample operates.

3.1 Loan Demand, Repayment and Late Fees

Figure 2 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 marketing campaign by Airtel on that day. Later, we 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 2 also shows that on-time repayment occurs for only about 38% of the loans. Overall, the share of principal recouped on the average loan is over 100%,

[21] This gap is similar to that reported in the most recent Findex (Demirgüç-Kunt et al. 2022) for Malawi, which reports a mobile money ownership rate of 30.3% for women and 38.8% for men. The percentage of female mobile money users is therefore about 43%.

meaning that the fees charged to those who do repay more than compensates for those who default.

Panel C of Table 1 shows statistics on loan usage, including 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 $\leq$0.001).

Figure A4 shows some statistics on what *Kutchova* is used for, as reported by borrowers. There is a lot of heterogeneity: while 29% of people use loans for airtime, 20% use them for 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 borrowers use them for medical emergencies).

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). This average level of repayment masks important heterogeneity in repayment behavior: only 38% of loans are fully paid back on time, another 47% are fully paid back late, 4% are only repaid in part, and 11% are not paid back at all.

Figure 1 plots a histogram showing when people pay back their loans. The figure shows that a large fraction of loans are repaid the day before the loan is due, which is likely due to the reminder SMS that borrowers receive 24 hours before the loan is due, which includes the exact due time and the 12.5% late fee. However, the figure also shows that a surprisingly large fractions of loans are fully repaid *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 therefore avoid these fees if they transferred the funds themselves on time, instead of letting Airtel do it on their behalf a few minutes *after* the deadline. Figure A5 zooms in on repayment behavior at the hourly level, and shows the "just-after-the-deadline" repayment at play for all deadlines (when the loan is first due after 15 days, when the second late penalty (an extra 10% fee) kicks in after 30 days, and when the loan becomes "in default" after 45 days).

Figure 4 shows information on how commonly people pay back loans late: we show the 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 40% if they cashed out the loan, given the 8% cashout fee).[22]

A final piece of motivation comes from an advertising campaign by Airtel. On a specific date in July 2019, Airtel informed eligible customers of the relaunch of the Kutchova loans, and as a result there was a surge in loan demand. Figure A6 presents loan demand (the yellow bars), and the subsequent repayment rate (the red dots) around the campaign (on July 23/24, 2019). We find that repayment rates were lower for those induced to borrow by the campaign, suggestive that people were responsive to marketing even if they lacked ability to repay. These marginal loans were not profitable for the lender, who recouped less than 100% of the principal on average.

3.2 Alternative Sources of Credit in Malawi

Our surveys 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.

The annualized interest rate on the more popular loans are all over 100% APR. 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

[22] At the loan level, 56.5% of loans that are *not* paid on time had insufficient funds on the account on the due date but are ultimately repaid fully at a later date; 19.50% of loans that are *not* paid on time are repaid late within a day, meaning that the funds were available and the borrower failed to initiate the payment on time. At the user level, among borrowers with at least 1 Kutchova loan not paid on time, 68% of individuals *never* repaid late while having funds on hand. Among borrowers with at least 2 kutchova loans over the period covered in our data, 53% of individuals *never* repaid late while having funds on hand, and 26% repaid late with funds on hand only once.

due in 1-2 weeks). Ten percent 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. 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. Finally about 1% of people took out loans from moneylenders, at about a 36% interest rate over 2 months (over 500% APR).

4 Impacts of Digital Credit Access: RDD Analysis

This section uses a regression discontinuity approach to estimate the reduced-form effects of digital credit access on a set of outcomes.

4.1 RD Sample and Design

Recall that for each eligible Airtel mobile money account owner, 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 ∼5% of those scored, corresponding to those with a predicted profitability of -0.14 and higher), were considered eligible.[23]

While some users qualified for a larger loan, the focus of the RDD 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 A7. 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.

[23] 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. The July relaunch was planned to be gradual, with subsets of each groups scheduled to become eligible in different weeks of July. In practice, just under 27,000 users got access to Kutchova in 2019—the rollout stalled due to the lender claiming limited liquidity. The distributions of scores are very similar across batches, suggesting that the score itself was not used to determine batches. In conversations with the scoring firm and Airtel, the decision to limit access was driven by lack of funding, and 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).

Figure 3 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 administrative dataset as having been granted eligibility (i.e., we observe them taking up a loan). Crossing the eligibility threshold causes a 34 percentage points increase in borrowing from *Kutchova*.

We construct an analysis sub-population of users around the threshold. We exclude existing users 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 granted access upon the relaunch. The resulting sampling frame for our regression discontinuity design analysis consists of around 10,000 users.

We use a robust non-parametric regression discontinuity approach, following Calonico et al. (2014). The running variable is the re-centered, continuous "predicted profit" variable that determined eligibility. We use all observations for estimating the treatment effects, employ a uniform kernel which gives equal weights to all observations, and use a linear specification for construction of trends. We also include controls from the Airtel administrative data which include 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. All estimates are weighted by sampling weights. We evaluate the validity of the RD design in Appendix B.

4.2 Regression Discontinuity Results

The first three columns of Table 3 examine the impact of credit eligibility on amounts borrowed through the schemes, using administrative data from Airtel. 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). The total amount borrowed increases by \$1.8 for the average eligible user, and \$2.2 for the average respondent in our survey sample.[24]

We use survey data to measure potential displacement effects on other sources of credit over the 3 months prior to the survey.[25] Column 4 of Table 3 shows effects on take-up of any non-Kutchova loan (digital airtime, friends/family, and VSLAs/ROSCAs). The point estimate is non-negative, which suggests that digital loans did not crowd out existing credit. Column 5 shows the total value of credit across all non-Kutchova sources, in dollars. The effect is positive but insignificant. The confidence interval is wide however, and the value of digital loans appears small relative to total credit (which is about $30).

Downstream Outcomes

Columns 6 to 8 of Table 3 show effects on relevant downstream outcomes. Columns 6 and 7 measure self-reported financial security. The dependent variable in Column 6 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 in Column 7 is a financial security index.[26] We find no effect on this index, which may not be surprising since a MWK 1,000 loan (around $1.4) 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). In Column 8, the dependent variable is an indicator equal to 1 if the respondent used digital credit as a source of cash to cope with shocks. 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).[27]

[24] We show pooled results in this table, and present results separately for women and for men in Table C1. The effects are observed for both gender, and somewhat more pronounced among females

[25] 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.

[26] See Table 3 notes for the details on how this index is constructed.

[27] We also attempted to collect data on total savings as reported by the respondent. When estimating impacts of eligibility on savings, we find that 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). When we focus on liquid savings, the coefficient is negative and fairly large (-$11, about 14% of the non-eligible mean), but, again, not statistically 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

Overall, 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 total amounts borrowed are 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.

Qualitative Evidence

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 4. 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; 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 did not fully incur the expense, or did not incur it at all. The remaining borrowers are split between borrowing elsewhere (26%) or using savings (15%). Both Panels A and B 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 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).

coefficients reflects anything causal; instead, we suspect the savings data is noisy. These results are available in the NBER Working paper version.

5 Experimental Results: Financial Literary RCT

Although the RD analysis shows modest effects on average, the widespread prevalence of late payment suggest a possible role for financial literacy. Table 4 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 (Robinson et al. 2022). If lack of knowledge about the costs of digital borrowing is a driver of suboptimal repayment behavior, informing people might influence repayment behavior among those who choose to borrow, or influence demand. To investigate this, we conducted an RCT with eligible borrowers.

5.1 Experimental Design and Randomization

The timeline of the RCT is shown in Figure A8. 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.[28]

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 D. The scenario involved a shopkeeper who was purchasing inventory for her shop, and was deciding between using a digital loan or other sources.[29] The Finlit module stated the 10% fee for taking out the loan, highlighted the fact

[28]Stratification variables were the relaunch batch to which the user was assigned, whether the respondent was eligible for loans higher than MWK 1,000 (as opposed to loans of MWK 1,000), gender, quantiles for year of birth, whether the respondent lived in an urban area, and several other administrative variables (whether the respondent was automatically enrolled in mobile money upon SIM card registration, and whether the respondent had more than one SIM card). This created 495 strata with 53 users on average (range 4 to 614).

[29]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. This module was designed before we were fully aware of the size of the loans that would be offered, and so ultimately focused on a larger loan size (10,000 MWK) than what was ultimately available (1,000 MWK). While we think that the general concept of the intervention was still meaningful despite this difference, we do acknowledge that the hypothetical loan size did not match the

that the customer would be charged a cash-out fee if they were to withdraw the loan in cash, 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%. 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%."[30]

Precisely because of the lack of transparency around late fees and high potential costs, the Finlit module discussed other financing options, 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, to the best of our knowledge, as of January 2023 Airtel had not yet started filing reports.

Respondents were incentivized to initiate the module via a MWK 500 incentive payment, paid out in airtime, conditional on having gone through the module.[31] 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.

reality of what was ultimately offered.

[30] 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 IPA sent SMSes to all those in the Finlit and InfoSMS groups to inform them of the current late fee schedule and warn them that Airtel can change late fees without informing customers.

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

In addition to the IVR module, the Finlit group also received three 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 did not complete the module. The second group (the "InfoSMS" group) received the same three text messages as the Finlit group, without the IVR quiz.

The third 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, to equalize the incentive payment, and to control for any general "advertising" or salience effect of being exposed to the existence of *Kutchova*. 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*. Finally, the fourth group was a pure control group.

The table below summarizes the experimental design. The comparison between Finlit and Control provides the combined effect of the financial literacy training, the costs information and the salience. The Salience treatment isolates the role of salience. The effect of information can be teased out by comparing the InfoSMS arm to the Salience arm. The effect of the financial literacy component can be estimated by comparing Finlit to InfoSMS.

Features of Experimental Treatments

	Treatment Arms:			
	(1)	(2)	(3)	(4)
	Finlit	InfoSMS	Salience	Control
Financial literacy training	✓			
Costs Information	✓	✓		
Salience	✓	✓	✓	

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 A9 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%). Among compliers, the median duration of the IVR call was 14 minutes, and the mean 13 minutes.[32] These rates are much higher than in other IVR studies of which we are aware; however, takeup is still far below 100% and thus will work against finding treatment effects. 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 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.

5.2 RCT Results

In our analysis, we focus on a selected set of summary indicators and indices that were preregistered in the AEA RCT Registry: knowledge, loan take-up, repayment, and default behavior. In the appendix, we discuss more detailed questions. 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 to provide some descriptive evidence on the consumer experience. For each outcome, we estimate the following regression:

$$y_i = \beta + \theta FinlitIVR_i + \alpha SalienceIVR_i + \delta InfoSMS_i + \phi X_i + \epsilon_i \tag{1}$$

where y is the outcome for individual i, and $Finlit$, $Salience$, and $InfoSMS$ are treatment indicators. X_i is a set of covariates including the stratification variables.[33] For each outcome,

[32] 40% of compliers completed the entire module, with an average call time of 16.5 minutes.

[33] For regressions using administrative variables, the following control variables are included: whether the customer is mobile money enabled at the time of registering the SIM card, age bracket and gender of the SIM card owner, whether the phone was registered in urban or rural area, whether the credit limit was above 1000 MKW, and the credit score based on which eligibility was determined. For regressions on borrowing, pre-treatment borrowing is included. For regressions using survey variables, the following controls were used: geographical region fixed effects (central, northern, southern), an indicator for owning multiple sim cards, and gender.

we present a p-value as well as an FDR-adjusted q-value (adjusted for the 15 hypotheses tested in the table – Anderson 2008). Results are shown in Table 5. Results with strata fixed effects are summarized in Appendix C, Table C2.[34] Baseline balance checks are performed in Table A2, Columns 1-3 and Appendix B, Table B3 and Table B4. There is some evidence of imbalance: in the pre-treatment period (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) (Table A2). Total pre-treatment amount borrowed is 6.2% higher for the Finlit group (p-value=0.087). For this reason, we use ANCOVA specifications and control for pre-treatment borrowing behavior in the relevant columns in Table 5 and Table A2.

5.2.1 Primary Results

Knowledge As expected, we see a large effect of Finlit on knowledge: Column 1 of Table 5 shows an increase of 0.322 standard deviations (highly statistical significant) in knowledge from Finlit, but no effect of the other treatments. Table A1 shows results for each of the questions that go into this index. Compared to the control group, the Finlit 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.[35] These effects are large relative to control means of 29.6%, 35.4%, 27.7%, and 53.6%. The results are similar by gender, as shown in Table C2. The null effect of the InfoSMS treatment on knowledge suggests that borrowers are inattentive to costs information delivered via SMS.

Loan demand Columns 2-3 of Table 5 shows our key measures of loan demand, an indicator for taking out a loan within 9 months, and the total amount borrowed. The Finlit intervention increases the likelihood of having taken at least one *Kutchova* loan in the subsequent 9 months by 1.9 percentage points, around a 5% increase from a base of 40% (p-value of 0.011, q-value of

[34] We prefer to control for stratification variables rather than 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 one of the treatment groups, so the effective sample size and precision with strata fixed effects is reduced.

[35] Averages for the control group in this table indicate lower awareness than what was shown in Table 4. 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.

0.058). The total amount borrowed over 9 months increases by \$0.576 (around a 9% increase from a base of \$6.58 (p-value of 0.029, q-value of 0.090). The Salience treatment has no discernible impact on loan take-up, which suggests that the Finlit effect is not driven by a marketing or salience channel.

We unpack these demand results in Table A2. This table shows the impacts on loan demand over 3 time periods: before the treatment began (Columns 1-3), which is included to show the pre-treatment (im)balance discussed above; 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. (Recall that columns 4-9 controls for pre-treatment take-up.) Columns 4-6 show an *increase* in loan demand 0-3 months post-treatment for respondents in the Finlit group. They are 3.3 percentage points more likely to take a loan (on a base of 25.3%) and take out about 0.11 more loans (an 18% increase on a base of 0.62). The total amount borrowed from *Kutchova* 0-3 months post-treatment is 14% larger (+0.296 from a base of 2.05) in the Finlit group (more than double the percentage gap pre-treatment). The impact of Finlit on demand is attenuated in the 3-9 months after treatment: respondents are 1.2 percentage points more likely to take out a loan over that window, and the total amount borrowed is 6% higher, but the treatment effects are not significant at conventional levels.

Loan Repayment Column 4 of Table 5 shows a loan-level regression, showing the probability of paying back the loan on time. We find a positive point estimate for both Finlit and Salience but neither are significant. Table A3 show effects on the full set of 5 measures of loan performance: in addition to the measure already shown, this includes 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 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 modestly improved some 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 Table A3 Column 2, Finlit borrowers are no less likely to pay back on time. Instead, it is because Finlit borrowers are less likely to fully default (Column 5). Overall, these results suggest that Finlit (modestly) improved outcomes for the lender.

Table A4 shows repayment behavior outcomes at the user-level. The Finlit group pays no more late fees as a percentage of borrowing (Column 1), but does pay more late fees in total because they take out more loans (Column 2). Finlit does not reduce the incidence of suboptimal repayment behavior. In fact, Finlit respondents are more likely to pay the late fee at least once (Column 3) and more likely to have paid the maximum late fee at least once (Column 5). There is no change in the likelihood of having repaid late but on the due date (i.e., having repaid via the auto-recovery feature which triggers the 12.5% penalty fee) (column 4).

We can look at loan repayment in another way, by exploiting the randomization of the date at which individuals sampled for one of the treatments were treated, which we present in Figure A10. 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.

Default Finally, Column 5 of Table 5 shows effects on the probability of default (at the borrower level). We find evidence that the Finlit group is more likely to be in default: the point estimate is 1.6 percentage points, +8% from a base of 19.7% (p-value of 0.015, q-value of 0.065). Evidently, this occurs because while the Finlit group is marginally more likely to pay back a loan on time, they take out more loans and have more of a chance for default.

5.2.2 Secondary Results

Regret and Attitudes regarding *Kutchova* In Table A6, 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.

Qualitative evidence on unexpected findings and threats to validity

The increase in loan demand was unexpected, and we attempted to gain more insight into this finding during our follow-up survey. In Table A7, we present descriptive statistics on what the respondents who completed the IVR Finlit module reported learning from it, when surveyed at follow-up (so about 3 months after the intervention). Just over 60% of respondents perceived the IVR quiz they participated in as providing information about Kutchova (Panel A), while 30% thought the core message was about responsible borrowing and financial management (Panel B).

Contrary to expectations, about 65% of Finlit respondents reported that the module made them think *Kutchova* was *less* expensive than they previously thought (and only 10% updated the other way) (Panel C). About 72% reported that *Kutchova* is less expensive than alternative sources of credit (Panel D). It may therefore not be surprising that roughly 64% reported that they were more likely to use *Kutchova* after taking the module, and only 19% less. We interpret this result as suggestive that people do not have much information on what the costs of *Kutchova* are, and the costs disclosed in the IVR module and accompanying SMS were not perceived as exorbitant. An alternative explanation would be 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. In addition, we see no difference in these responses based on whether respondents had taken a *Kutchova* loan prior to the Finlit intervention.

6 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.

Table 6 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 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—the two dates on which we observe a surge in borrowing in response to an advertisement campaign by Airtel.

Panel B of Table 6 exploits the survey data to look at other correlates of arguably sub-optimal 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 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. They use the loan for convenience, and are inattentive to the terms.

7 Conclusion

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 and take out loans without knowing details of the terms, and many end up paying late, incurring large fees.

We examine the effects of digital credit in Malawi 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 digital credit 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 $1.4). 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.

With this concern in mind, 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. We find that this intervention modestly *increased* demand for loans but had no effect on the likelihood of default on a single loans, and therefore ultimately increased the proportion of borrowers who defaulted on at least one loan (since borrowers took out more loans).

We designed the study to separately analyze effects for men and for women. We see dramatic differences in mobile money usage by gender: women make up only 41% of Airtel users, and 36% of those eligible for digital loans. While there is an active debate about how digital financial services may ameliorate or worsen gender disparities in financial access, in our study we find minimal differences by gender in this specific context. Both the estimated effect of access in the RDD, and the impacts of the financial literacy training, are statistically indistinguishable between men and women.

If digital credit is to expand in Malawi, our results raise some important consumer protection questions. In particular, the consequences of default depend on whether borrowers are reported to credit bureaus (as well as how much consumers value their credit score, in particular, whether they expect to have access to other loans in the future). Currently, the mobile network operator threatens borrowers with reporting, but reportedly does not actually report.

While our research design is focused primarily around the borrower, the results also speak to effects for the lender. Because default is common (15% of loans are not repaid in full), at the current nominal interest rate of 10%, the product is likely only profitable because about half of loans are paid back fully but late, and are charged sizeable late fees.[36] Potentially, the lender therefore has an incentive to screen not on creditworthiness but on propensity to pay back late: the ideal borrower is one who has the means to repay but is inattentive to fees. Absent oversight, the lender may choose to shroud fees, which is exactly what we observe: during this time period, the lender charged fees far above their advertised level (12.5% instead of 2.5%). This lack of transparency raises serious concerns about the potential for predatory behavior by lenders offering expensive but easily accessible credit products.

[36] However, calculating profitability is complicated by the fact that the loans themselves are financed by a bank but are transacted on the MNO network. The MNO earns profits on transaction fees, and many digital loans are used to purchase airtime.

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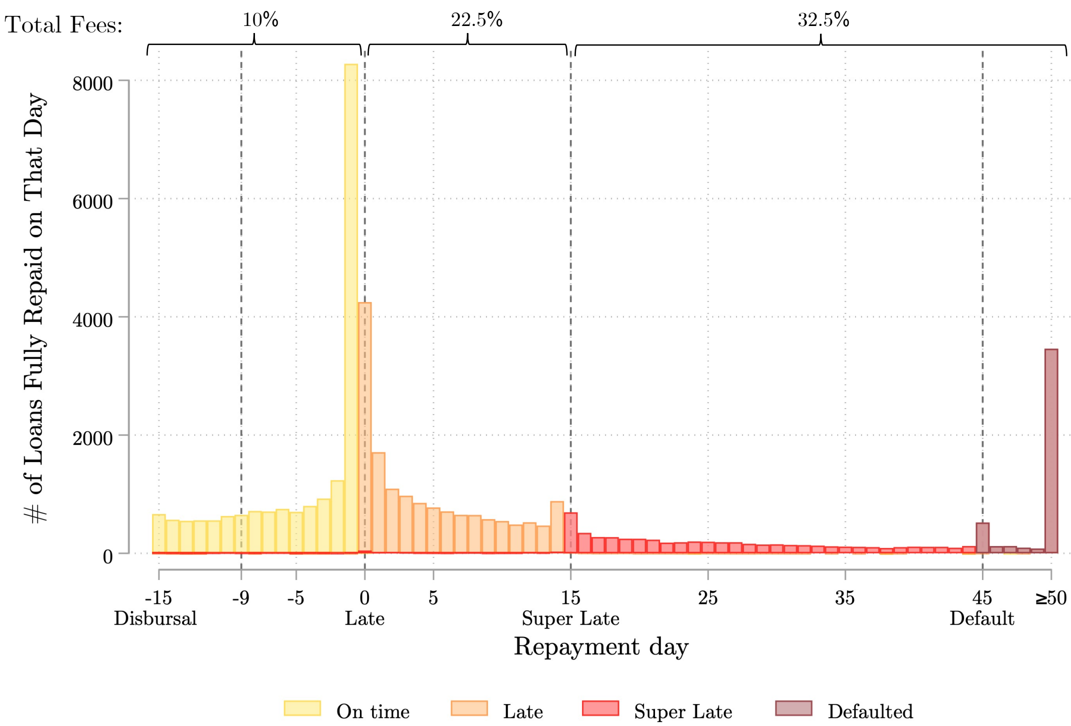
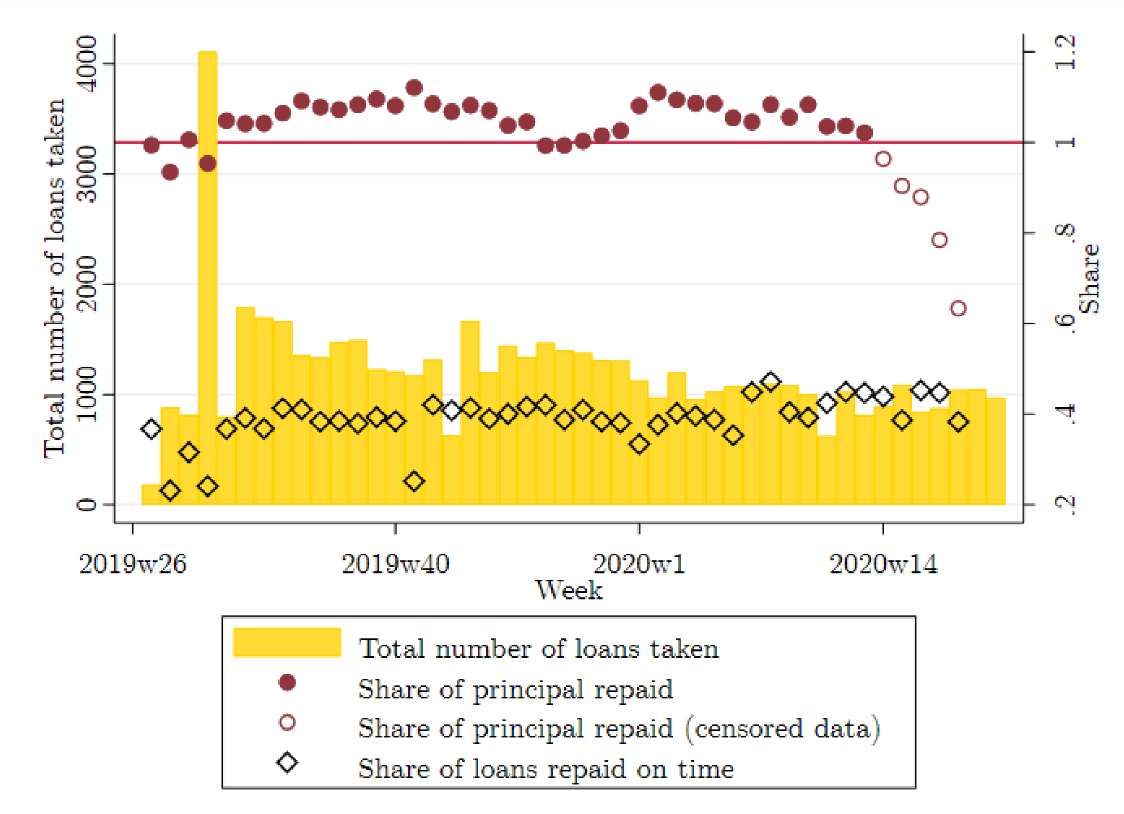
Figure 1: Repayment behavior: Timing and Total Fees Paid



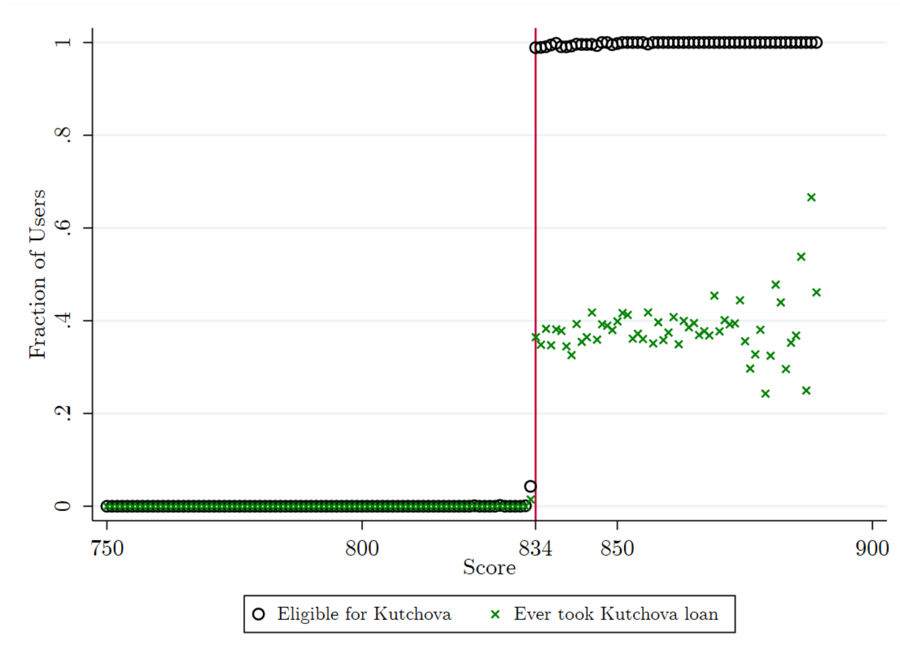
Notes: Source: Administrative Data on Kutchoval loans obtained from Airtel. Unit of observation: Loan. Loans with incomplete reimbursement information (missing disbursal or repayment date) and loans taken in the 8 weeks preceding May 20, 2020 (when the data was shared with the research team) are dropped 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 2: Take Up and Repayment of Kutchova Loans Over Time



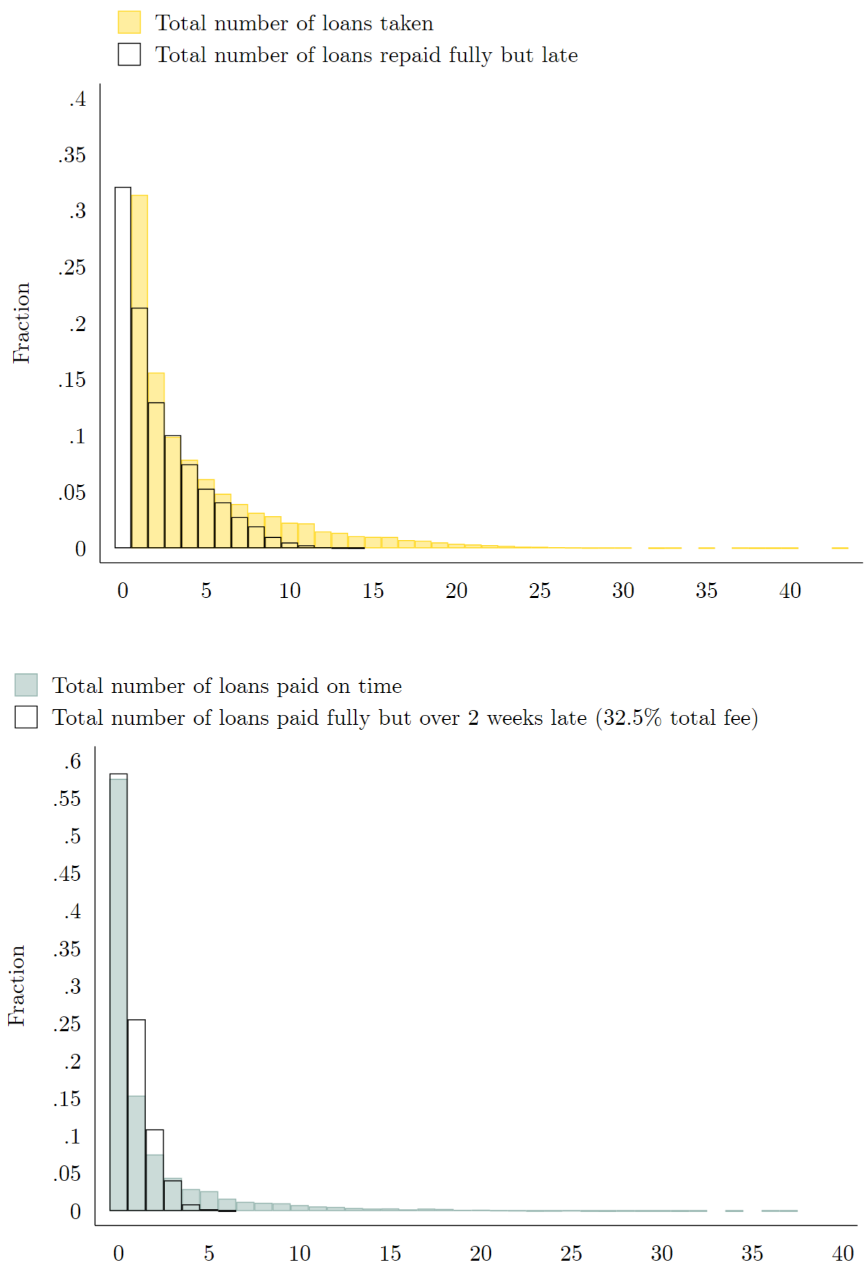
Notes: Source: Administrative Data on Kutchoval loans obtained from Airtel. Information on loan repayment for loans taken in the 8 weeks preceding May 20, 2020 (when the data was shared with the research team) is truncated (censored) since some borrowers take up to 8 weeks to repay in full. This explains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

Figure 3: Eligibility and Take-up of Kutchova by Score



Notes: Data Source: Administrative data. Eligibility for loans was determined by a third-party credit scoring firm, which scored based on mobile money usage. Sample exclude customers with a credit limit above MWK 1,000. Existing Kutchova users excluded since they were scored using a different algorithm which also included their prior repayment history, and we do not have access to their scores.

Figure 4: Repeat borrowing with late fees



Notes: Data Source: Administrative Data. Unit of observation: individual user eligible for loan from Kutchova and included in Kutchova relaunch. 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 borrower paid total fees of 33.5% (22.5% in late fees in addition to the original 10% facilitation fee).

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
Total value of late fees paid (USD) (uncond.)				0.77	0.62	0.82	<0.001
Total value of late fees paid (USD) (if ever used)				1.73	1.44	1.83	<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 . 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. 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. For reference, *Kutchova* has a fee of 10% over a period of 15 days.

Table 3: Regression Discontinuity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Administrative Data			Survey Data				
	Kutchova Amount Borrowed (USD)			Credit Use in Past 3 Mo		Financial Security		
	Full Sample	Survey Sample		Survey (2) Sample		Survey Sample		
	Since July 2019	Since July 2019	In 3 Months Prior to Survey	Took a Non-Kutchova Loan	Non-Kutchova Amount Borrowed (USD)	Satisfied with Financial Well-being	Financial Security Index	Used Kutchova to Cope with Shock (if any)
Above credit eligibility threshold	1.77	2.24	0.54	0.07	1.28	0.12	-0.02	0.00
	(0.19)	(0.28)	(0.09)	(0.05)	(5.92)	(0.04)	(0.04)	(0.00)
	{<0.001}	{<0.001}	{<0.001}	{0.202}	{0.829}	{0.002}	{0.639}	{0.661}
Observations	10,768	3,996	3,996	2,855	2,855	3,996	3,992	2,809
Mean (non-eligible)	0.01	0.02	0.01	0.59	29.87	0.55	0.38	0.00
Mean (eligible)	2.16	2.48	0.63	0.67	29.83	0.60	0.34	0.00

Data source: Columns 1 to 3: 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). Columns 4 to 9: Phone Survey with a subset of mobile money users with a credit score between 827 and 842 and a credit limit of MWK 1,000. 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 to 8 is restricted to the sample who completed the survey, and sampling weights are applied. In columns 4 to 5, the sample is further restricted to those administered version 2 (=RD) of the survey since version 1 did not include information on past three months (only last loan). In all columns, 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. In columns 2 to 8, we additionally control for the covariates from the survey shown in Table B2, region, and shocks experienced in the past 3 months. Missing values for covariates are replaced by 0 and indicated by a dummy. "Took a Non-Kutchova Loan" and "Total Non-Kutchova Amount Borrowed" exclude very uncommon credit sources such as moneylenders and MFIs. The "Financial Security Index" is derived from: ability to pay for non-food expenses (4 variables: payments for health expenditures, bill payments, school fees and ability to help family/friends in time of need), food security (4 variables: relying on less expensive foods, limiting meal sizes, reducing number of meals and borrowing food), and degree of preparation for future emergencies (4-point scale). We compute indices using weighted averages and standardizing against the non-eligible group. Monetary outcomes are reported in USD and winsorized at 1% in columns 2 and 3, and at 5% in column 5. Standard errors in parentheses, p-values in curly brackets.

Table 4: 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
It helps deal with emergencies/financial distress	0.003	0.003	0.001	0.85	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 IVR treatment. Sampling weights applied.

Table 5: Impact of Financial Literacy Intervention on Key Outcomes

	(1) Knowledge Index	(2) Took Kutchova Loan	(3) Amount Borrowed	(4) Loan Fully Paid Back on Time	(5) In Default
Finlit	0.322	0.019	0.576	0.016	0.016
	(0.060)	(0.008)	(0.263)	(0.012)	(0.006)
	{<0.001}	{0.011}	{0.029}	{0.199}	{0.015}
	[0.001]	[0.058]	[0.090]	[0.349]	[0.065]
Salience	0.040	0.004	0.079	0.017	0.008
	(0.058)	(0.008)	(0.260)	(0.013)	(0.006)
	{0.492}	{0.603}	{0.761}	{0.186}	{0.209}
	[0.641]	[0.686]	[0.828]	[0.349]	[0.349]
InfoSMS	0.067	-0.004	0.184	-0.013	-0.001
	(0.071)	(0.008)	(0.281)	(0.014)	(0.007)
	{0.345}	{0.598}	{0.512}	{0.350}	{0.927}
	[0.487]	[0.686]	[0.641]	[0.487]	[0.928]
Observations	3,321	26,467	26,467	44,907	26,467
Mean of Control	0.024	0.406	6.584	0.413	0.197
SD of Control	1.042	0.491	16.960	0.492	0.398
P-val Finlit=Salience	0.000	0.046	0.062	0.924	0.241
q-val Finlit=Salience	0.001	0.115	0.141	0.928	0.378
P-val Finlit=InfoSMS	0.000	0.004	0.173	0.036	0.020
q-val Finlit=InfoSMS	0.002	0.027	0.349	0.101	0.073

Data Source: RCT Survey (Column 1) and administrative Kutchova data (Columns 2-5). Unit of observation: individual user (columns 1, 2, 3, and 5) and loan (column 4). Columns 2-5: Sample include all Airtel customers eligible for loans as of the July 2019 relaunch.

Notes: Each column corresponds to a separate OLS regression. Robust standard errors are reported in parentheses, p-values in curly brackets, and adjusted q-values following FDR correction for multiple hypothesis testing in square brackets. The knowledge index (Column 1) is based on survey data collected 2 to 3 months after the intervention; it is constructed from the variables shown in Table A1, using a GLS weighting procedure following Anderson 2008 and is standardized against the control group. Dependent variables in columns 2 to 5 are from administrative Kutchova data over the 9 months following the intervention. Amount of loans taken (Column 3) is expressed in USD and winsorized at 1% level. The control variables for survey and administrative data are described in footnote. In addition, controls for loan outcomes in Columns 2 and 3 include pre-treatment borrowing amount. Controls for column 4 include pre-treatment borrowing and the total amount borrowed. "In default" (Column 5) is a binary variable for whether the person defaulted on their last loan and is now ineligible for loans. Sampling weights are applied in column 1 only.

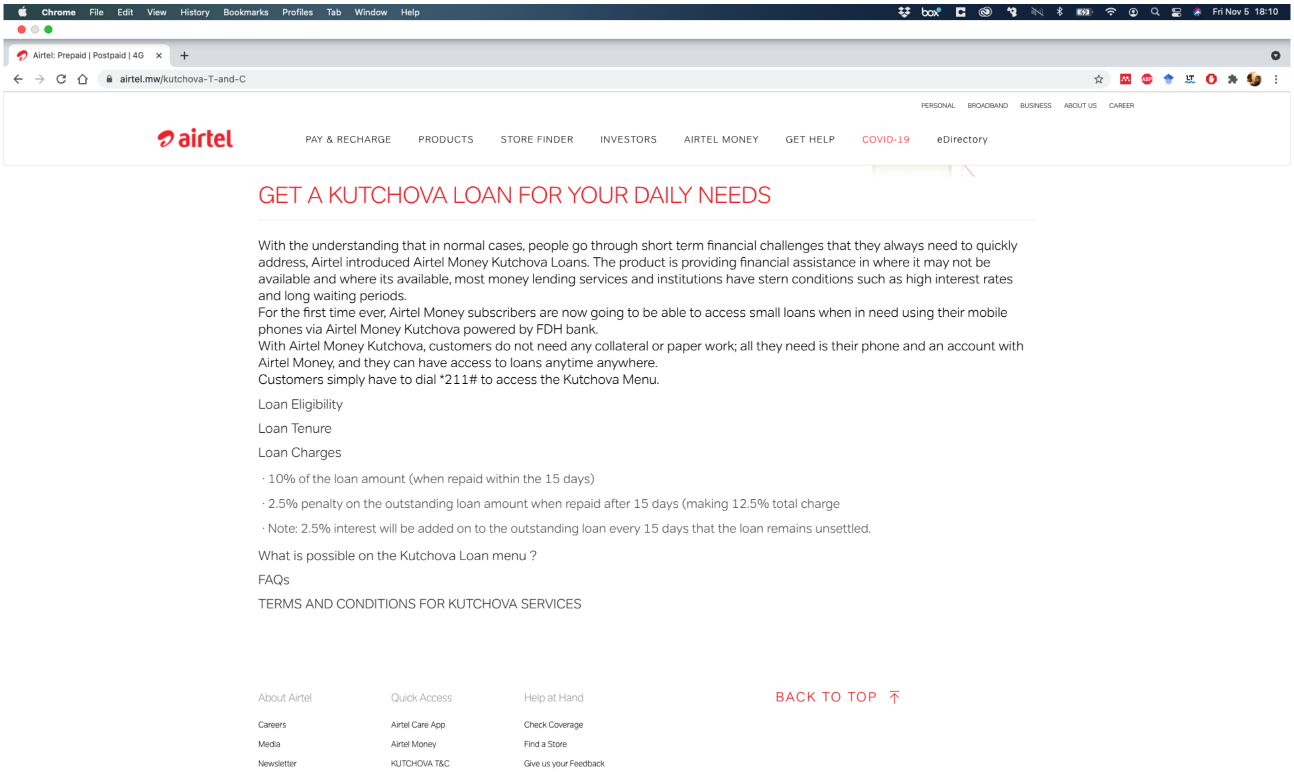
Table 6: Covariates of Borrowing Behavior

	(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: Within each panel, each column corresponds to an OLS regression. Sample restricted to those newly eligible for Kutchova as of July 2019 and given a credit limit of MWK 1,000. Sampling weights applied in Panel B. Column 5 has fewer 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).

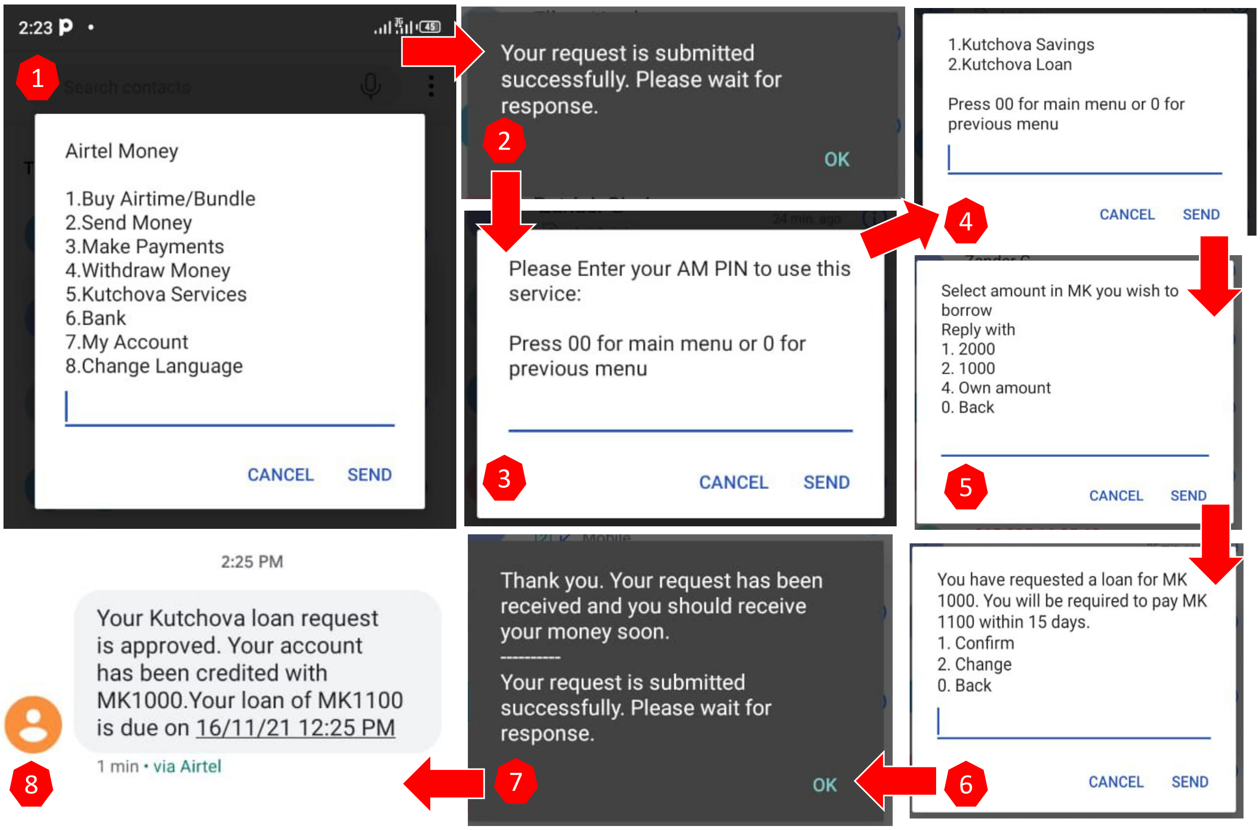
Appendix A: Appendix Figures and Tables

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.

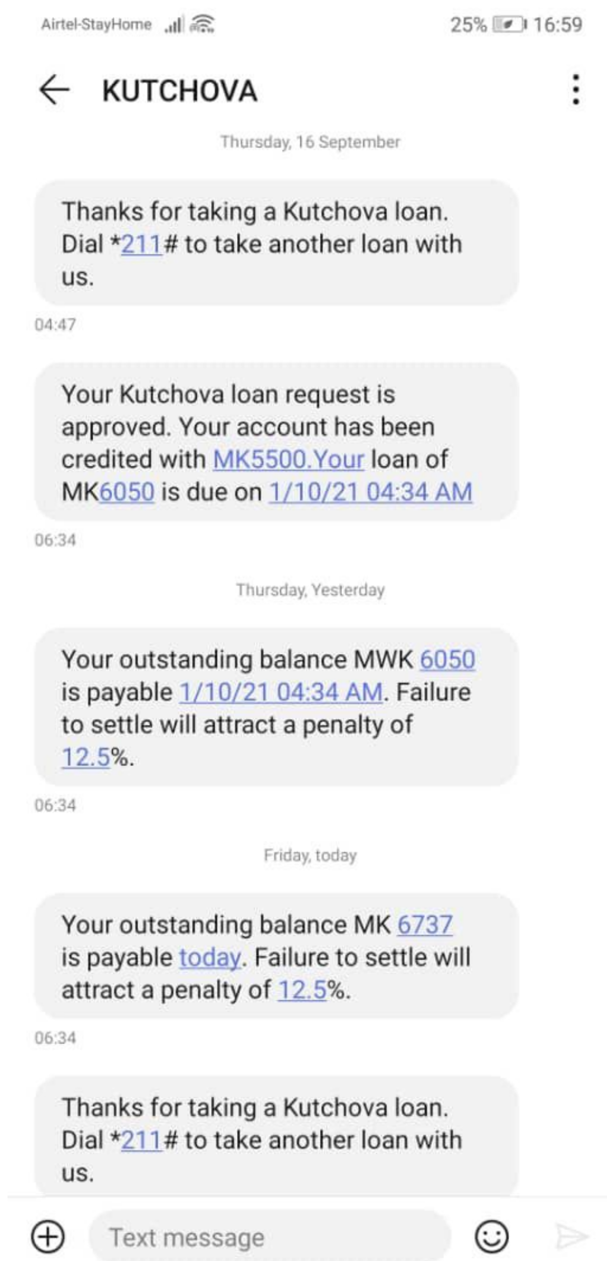
Acceptance of the Terms and Conditions is implied when customers request a loan. See T&C (website https://airtel.mw/kutchova-T-and-C) item 2.3:

"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

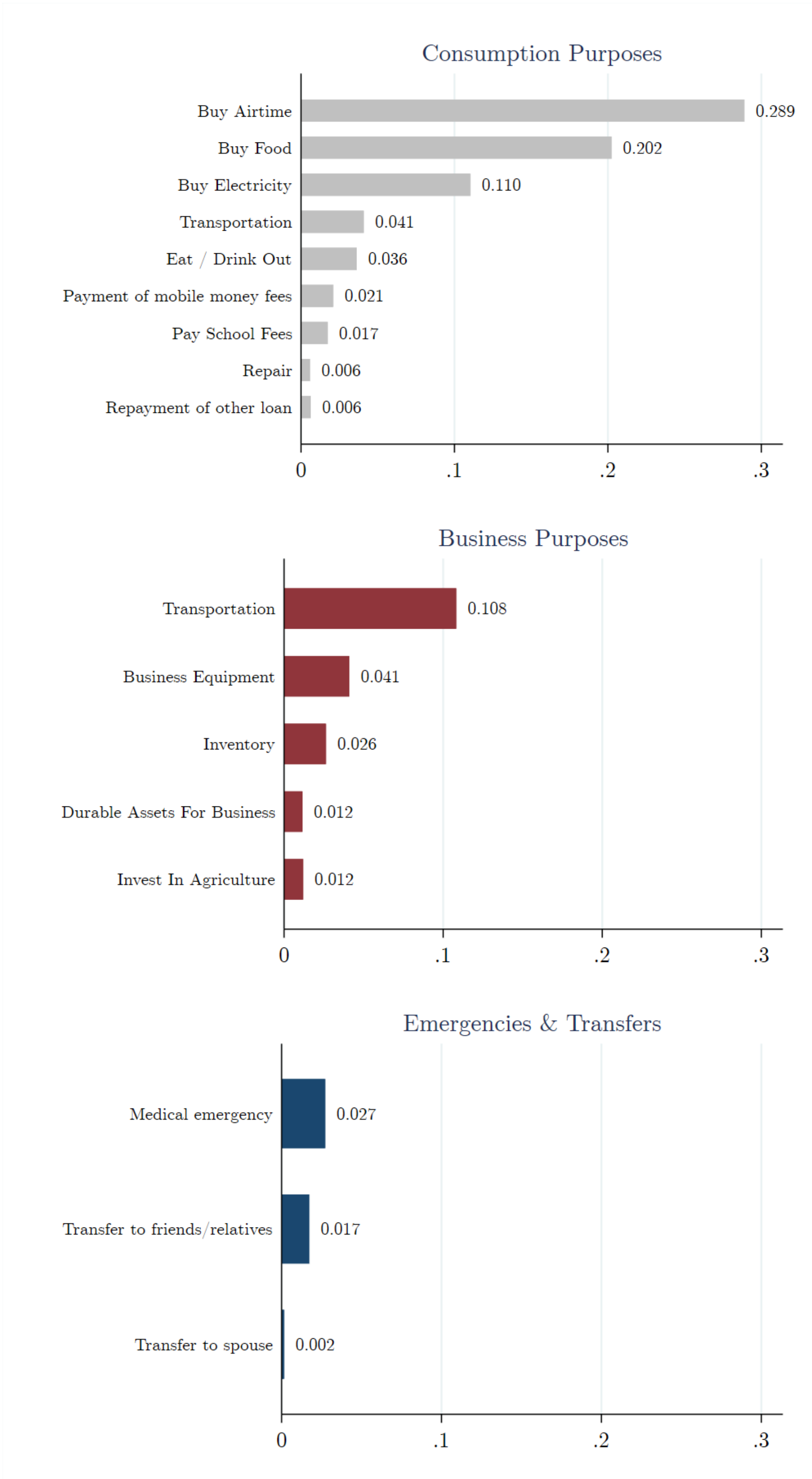
2.3.2. by using or continuing to use and operate the Kutchova services."

Figure A3: Late Fees Warning Text from Airtel



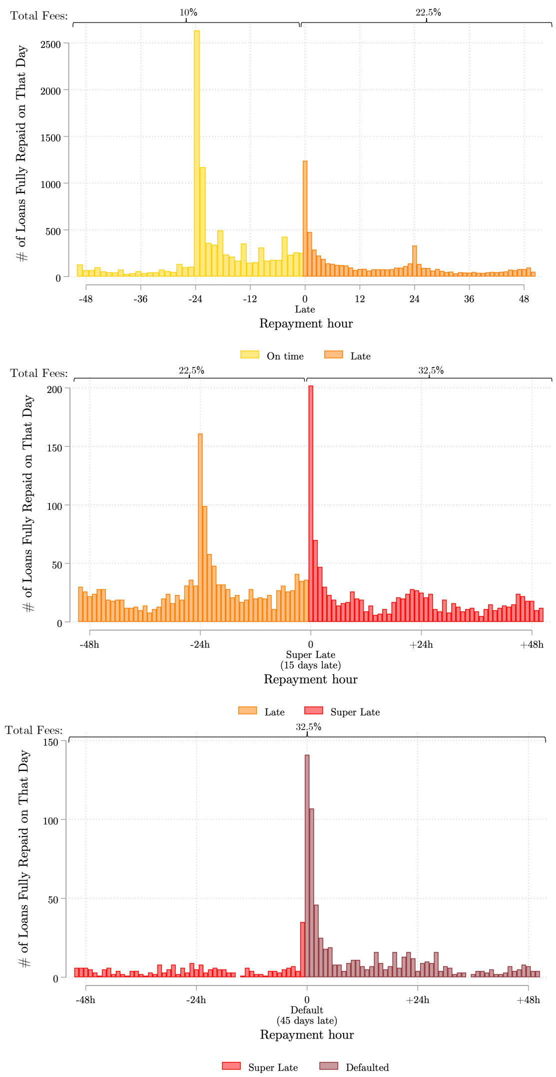
Notes: Screenshot taken on October 1st, 2021. 22 hours before the loan due time, customers receive a warning text from Airtel indicating that the late fee penalty would be 12.5%. The customer failed to repay on time, so Airtel added the 12.5% fee and sent a text message shortly after to encourage the 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 were the main uses for the last Kutchova loan?

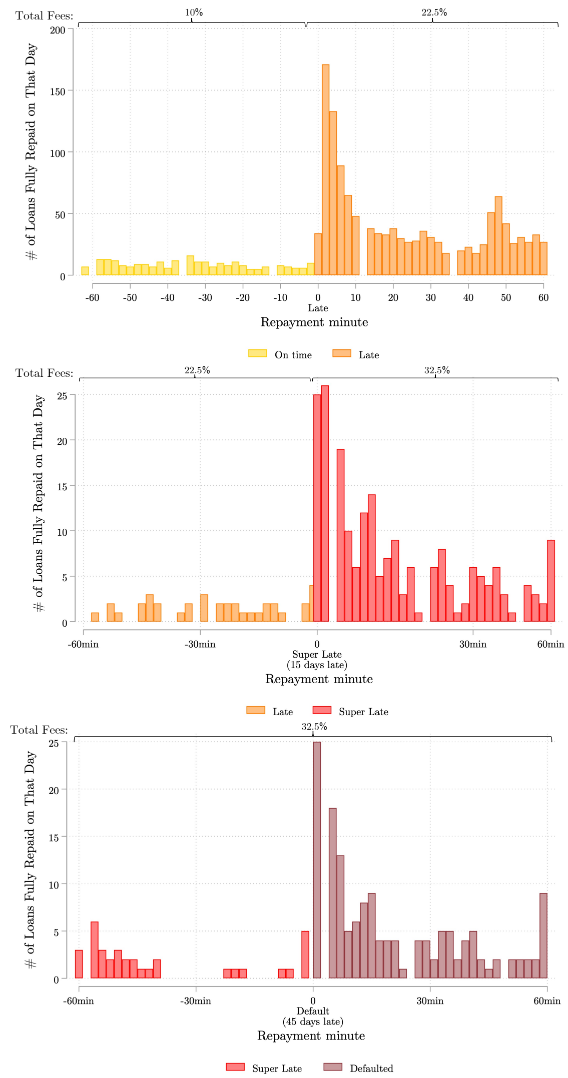


Notes: Data source: RCT Survey. Sampling weights applied. The respondent was asked the question "What were the main uses for your last Kutchova loan" and allowed to select multiple uses. Purposes are organized by categories for clarity of exposition.

Figure A5: Repayment Patterns & Auto Recovery



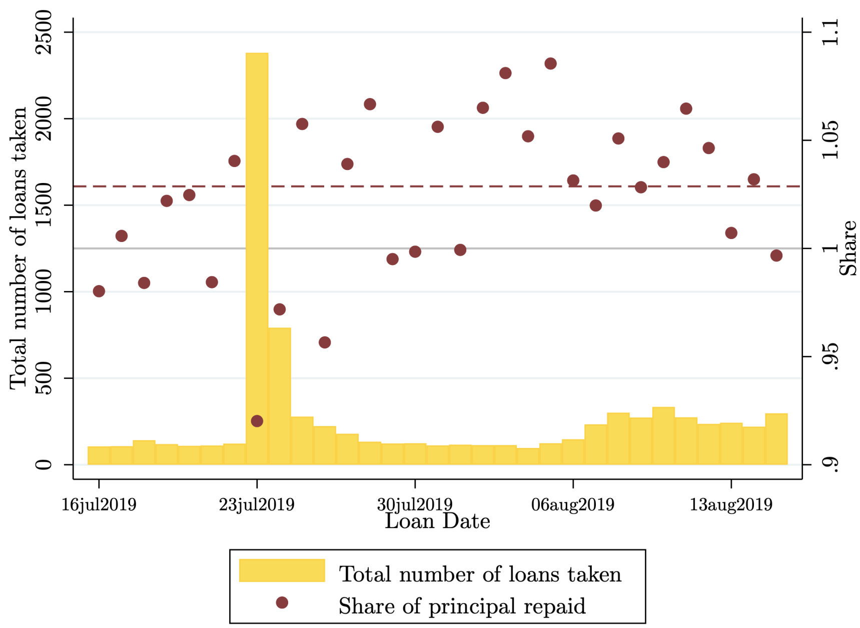
(a) Repayments Within 48h of Due Hour



(b) Repayments Within 60min of Due Minute

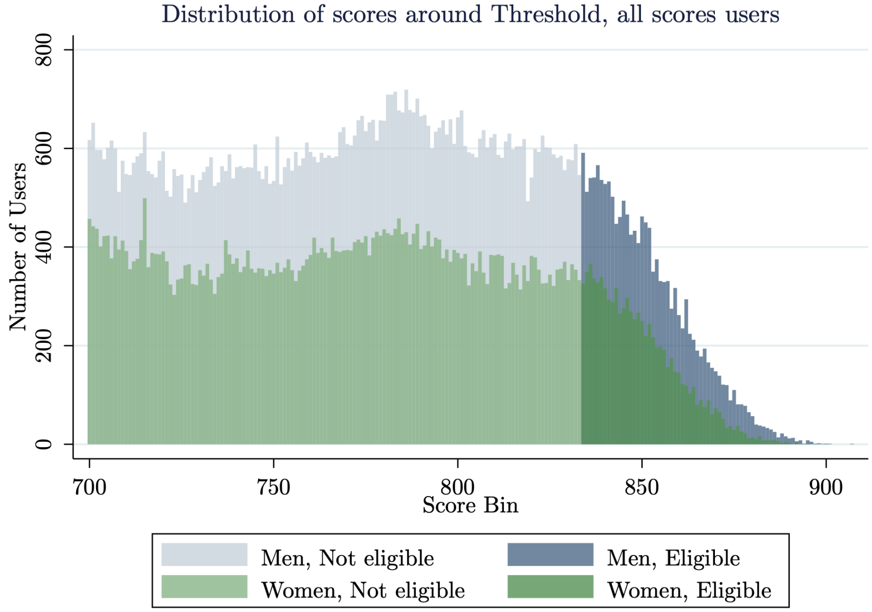
Notes: Source: Administrative Data on Kutchova loans obtained from Airtel. Unit of observation: Loan. Loans taken in the 8 weeks preceding May 20, 2020 (when the data was shared with the research team) are dropped since some borrowers take up to 8 weeks to repay in full. The final sample is composed of almost 44,000 loans. **Top Row:** 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. **Second Row:** 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. **Third Row:** 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 A6: Repayment Levels by Day, July 16 to August 15, 2019



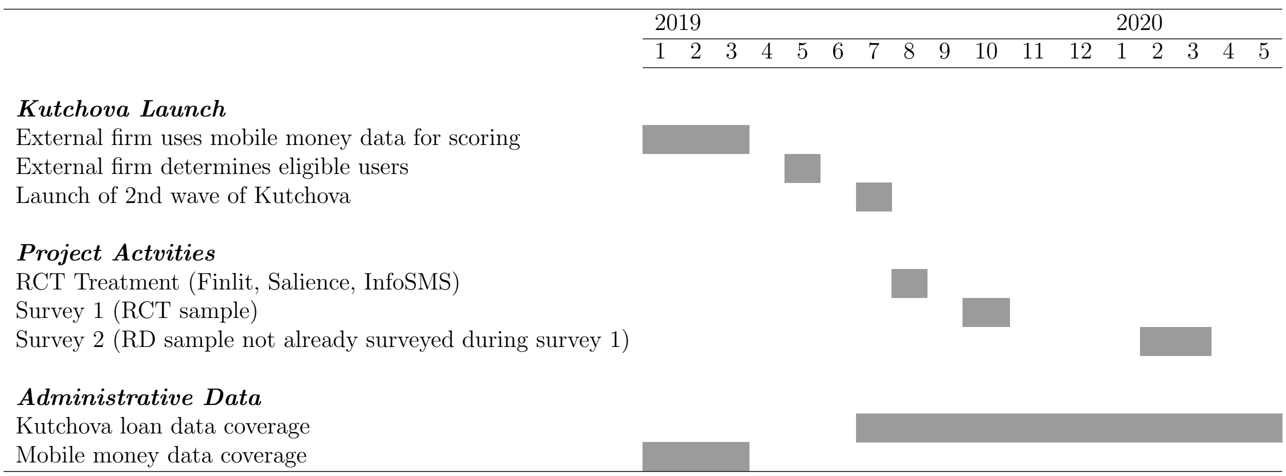
Notes: Dashed line shows the average share of principal repaid for the period shown, excluding loans taken on July 23 or July 24. The share of principal repaid among loans taken on July 23 is 10 percentage points lower (p-value<0.001) than the average share repaid across all other days shown, and 8.6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

Figure A7: 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 who were determined to be eligible for a MWK 1,000 loan. The figure excludes existing users, those with a credit score under 700, and those who qualified for a loan >MWK 1,000.

Figure A8: 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 A9: First-stage for Finlit RCT, by Gender

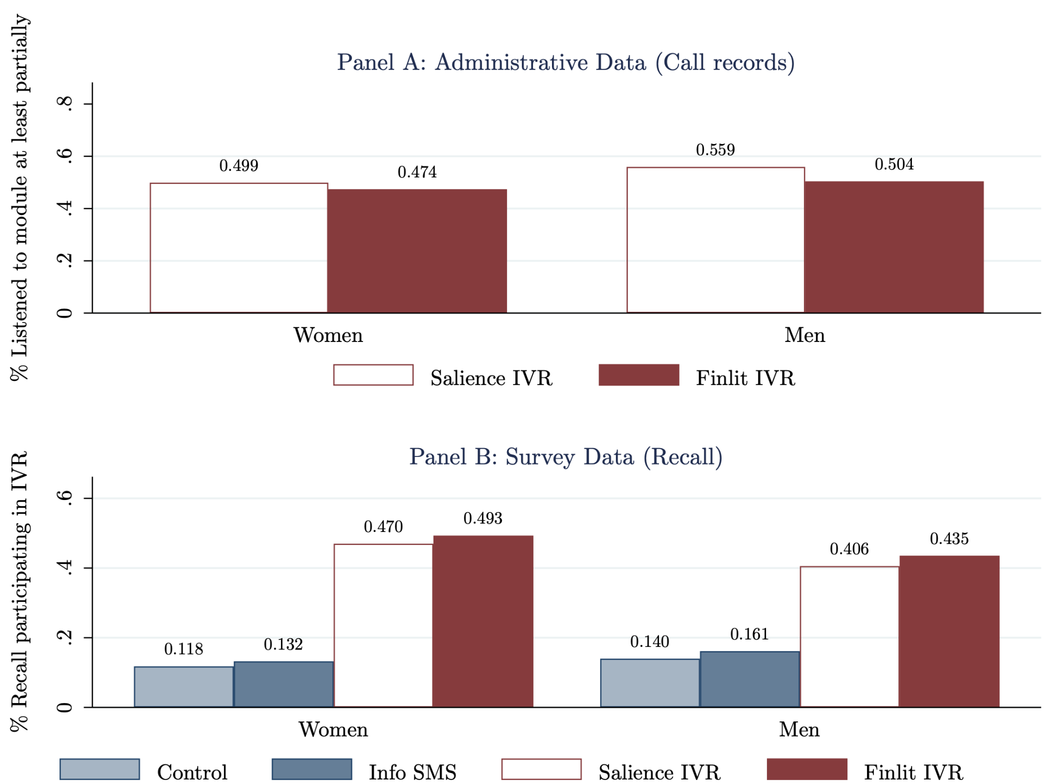
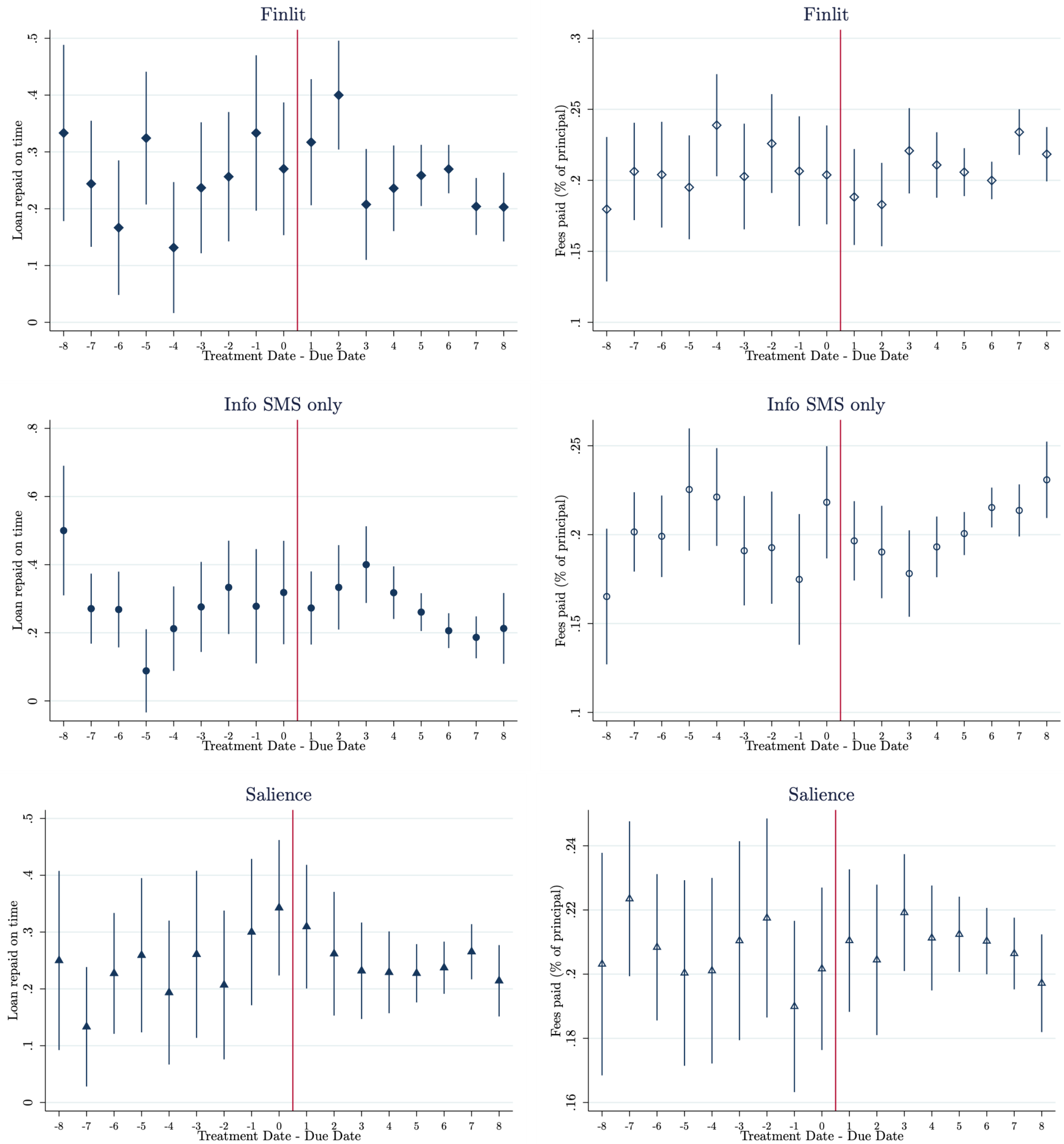


Figure A10: RCT Event Study: No Impact on Outstanding Loans



(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).

Table A1: 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
Finlit vs. Salience	0.125	0.106	0.092	-0.098	0.003	0.067	0.026	0.018
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, 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 A2: 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	0.033	0.111	0.296	0.012	0.094	0.280
	(0.007)	(0.010)	(0.036)	(0.007)	(0.023)	(0.081)	(0.007)	(0.042)	(0.200)
	{0.008}	{0.007}	{0.087}	{0.000}	{0.000}	{0.000}	{0.105}	{0.026}	{0.163}
Salience	0.009	0.014	0.050	0.009	0.014	0.072	-0.001	0.019	0.007
	(0.007)	(0.010)	(0.036)	(0.007)	(0.021)	(0.079)	(0.007)	(0.042)	(0.198)
	{0.197}	{0.155}	{0.162}	{0.187}	{0.499}	{0.366}	{0.892}	{0.653}	{0.971}
InfoSMS	-0.003	0.001	-0.011	0.010	0.025	0.142	-0.006	0.004	0.042
	(0.008)	(0.011)	(0.039)	(0.007)	(0.023)	(0.086)	(0.008)	(0.045)	(0.215)
	{0.739}	{0.927}	{0.777}	{0.167}	{0.264}	{0.099}	{0.415}	{0.924}	{0.846}
Observations	26,467	26,467	26,467	26,467	26,467	26,467	26,467	26,467	26,467
Mean of Control	.226	.287	.940	.253	.615	2.05	.293	1.089	4.209
Finlit vs. Salience	0.010	0.013	0.011	0.024	0.096	0.224	0.013	0.075	0.272
P-val Finlit=Salience	0.172	0.200	0.757	0.001	<0.001	0.006	0.080	0.085	0.177
P-val Finlit=InfoSMS	0.005	0.018	0.065	0.002	<0.001	0.084	0.021	0.055	0.278

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 was collected. All regressions control for the launch batch to which the user was assigned by Airtel, 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 A3: 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)	(0.012)	(0.010)	(0.002)	(0.005)
	{0.114}	{0.199}	{0.499}	{0.518}	{0.022}
Salience	-0.000	0.017	-0.015	0.001	-0.004
	(0.006)	(0.013)	(0.011)	(0.003)	(0.005)
	{0.935}	{0.186}	{0.161}	{0.602}	{0.440}
InfoSMS	0.008	-0.013	0.016	-0.002	-0.002
	(0.006)	(0.014)	(0.011)	(0.003)	(0.005)
	{0.219}	{0.350}	{0.162}	{0.560}	{0.755}
Observations	40,338	44,907	44,907	44,907	44,907
Mean of Control	1.057	0.392	0.466	0.031	0.112
Finlit vs. Salience	0.010	-0.001	0.008	0.000	-0.007
P-val Finlit=Salience	0.094	0.924	0.454	0.915	0.140
P-val Finlit=InfoSMS	0.826	0.036	0.045	0.228	0.071

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 was collected. All regressions control for the relaunch batch to which the user was assigned, 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 clustered at the individual level, p-values in curly brackets.

Table A4: RCT Analysis: Impact of Finlit on Credit History (User-Level)

	(1)	(2)	(3)	(4)	(5)	(6)
	Late Fees paid (% of total borrowed)	Late Fees paid (Total)	Paid Late Fees More Than Once	Repaid ≥ 1 loan late but on due date	Paid Max Fee At Least Once	After 9 months: In Default
Finlit	-0.002	0.072	0.013	-0.002	0.009	0.016
	(0.002)	(0.049)	(0.005)	(0.003)	(0.004)	(0.006)
	{0.463}	{0.137}	{0.004}	{0.511}	{0.047}	{0.015}
Salience	-0.000	0.011	0.007	0.000	0.002	0.008
	(0.002)	(0.050)	(0.005)	(0.003)	(0.004)	(0.006)
	{0.859}	{0.823}	{0.141}	{0.893}	{0.615}	{0.209}
InfoSMS	0.002	0.074	0.003	-0.002	0.007	-0.001
	(0.002)	(0.055)	(0.005)	(0.003)	(0.005)	(0.007)
	{0.270}	{0.179}	{0.504}	{0.567}	{0.131}	{0.927}
Observations	9,925	9,925	26,467	24,194	26,467	26,467
Mean of Control	.142	1.653	.077	.026	.066	.172
Finlit vs. Salience	-0.001	0.061	0.007	-0.002	0.006	0.008
P-val Finlit=Salience	0.576	0.202	0.155	0.428	0.138	0.241
P-val Finlit=InfoSMS	0.072	0.978	0.046	0.981	0.755	0.020

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 was collected. All regressions control for the relaunch batch to which the user was assigned, 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 A5: RCT Analysis: Impact on Loan Purpose and Other Credit Sources

	(1)	(2)	(3)	(4)	(5)	(6)
	Used Kutchova for			=1 if took	Number of loans	
	Consumption	Business	Emergency	Non-Kutchova Loan	Family/Friends	VSLA/ROSCA
Finlit	0.019	0.005	0.002	-0.005	-0.052	0.049
	(0.015)	(0.008)	(0.004)	(0.065)	(0.055)	(0.028)
	{0.203}	{0.522}	{0.669}	{0.943}	{0.336}	{0.083}
Salience	0.017	-0.005	-0.003	0.071	-0.006	0.082
	(0.015)	(0.007)	(0.003)	(0.082)	(0.073)	(0.030)
	{0.247}	{0.452}	{0.396}	{0.383}	{0.937}	{0.007}
InfoSMS	0.028	0.013	-0.001	0.065	0.019	0.051
	(0.021)	(0.012)	(0.005)	(0.086)	(0.075)	(0.037)
	{0.176}	{0.264}	{0.867}	{0.454}	{0.798}	{0.169}
Observations	3,145	3,145	3,145	3,321	3,286	3,307
Mean of Control	.068	.018	.005	.561	.437	.126
P-val Finlit=Salience	0.894	0.074	0.216	0.293	0.477	0.239
P-val Finlit=InfoSMS	0.639	0.464	0.612	0.391	0.317	0.964

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, 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). 'Took a Non-Kutchova Loan" is equal to 1 is the respondent took a loan from family, friends, Village Savings and Loan Association (VSLA) or ROSCA in the past 3 months. Robust standard errors in parentheses, p-values in curly brackets.

Table A6: RCT Analysis: Sentiment Towards Kutchova Product (if Ever Borrowed)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ever Regretted Taking out Kutchova Loan	Likes Kutchova Product	Dislikes: Tempted to Take Unnecessary loan	Dislikes: Interest Rate Higher than Other Options	Would Use Kutchova Loan for 1,000MWK Emergency	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
Finlit vs. Salience	-0.041	0.028	0.013	-0.015	0.051	0.022
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 A1 notes for list of controls included. Robust standard errors in parentheses, p-values in curly brackets.

Table A7: Finlit Intervention: Participants' Impressions

	(1) Mean
Panel A. In your own words, describe what the [FinLit IVR] quiz is designed to teach or reinforce?	
Saving/Responsible Borrowing	0.304
Information about Kutchova	0.618
Information about Airtel Money more generally	0.057
Panel B. What information did you learn?	
Kutchova Terms and Conditions	0.579
Kutapa Terms and Conditions	0.059
Financial Management	0.312
Information about Airtel	0.036
Panel C. Do you think Kutchova is more/less/equally expensive as what you thought before?	
More Expensive	0.100
Less expensive	0.647
Equally Expensive	0.254
Panel D. Do you think Kutchova is more/less/equally expensive as other sources of credit you could get?	
More Expensive	0.102
Less expensive	0.723
Equally Expensive	0.175
Panel E. After participating, are you more/less/equally likely to take a Kutchova Loan?	
More Likely	0.636
Less Likely	0.188
Equally Likely	0.176

Notes: Data source: Phone follow-up survey conducted in October 2019. Sample limited to respondents who completed the Finlit module (N=392). Prior to being asked the questions shown in the table, respondents were told: "Our system shows that you participated in a quiz which was a story about a shopkeeper Mary, and you were asked to make financial decisions on her behalf. The quiz started with "This is an interactive learning tool designed to teach about Airtel Money....". Do you remember taking part in this quiz?". 64% said yes. Those where then told "I am now going to ask you about your experience with this quiz" and asked the questions.

Appendix B: Study Design Validity Checks

B1. RD Design

We first evaluate the validity of our RD design by running the RD specification for a limited number of pre-period covariates which are available in the Airtel KYC and adminstrative data. Results are presented in Table B1. 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 B2 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 B2 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.

Table B1: 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 3 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 B2: 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.

B1. RCT Design

We show balance (separately by gender) on the administrative (Table B3) and survey (Table B4) variables used to check balance in the RD analysis. We find no evidence that our randomization failed to generate comparable groups.

Table B3: 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

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 A1 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 B4: 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, 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.

Appendix C: Results by Gender

Table C1: Regression Discontinuity Analysis By Gender

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Administrative Data			Survey Data				
	Kutchova Amount Borrowed (USD)			Credit Use in Past 3 Mo		Financial Security		
	Full Sample	Survey Sample		Survey (2) Sample		Survey Sample		
	Since July 2019	Since July 2019	In 3 Months Prior to Survey	Took a Non-Kutchova Loan	Non-Kutchova Amount Borrowed (USD)	Satisfied with Financial Well-being	Financial Security Index	Used Kutchova to Cope with Shock (if any)
Panel A: Females								
Above credit eligibility threshold	1.63	1.91	0.49	0.18	11.45	0.08	0.03	0.00
	(0.27)	(0.39)	(0.13)	(0.09)	(11.33)	(0.06)	(0.07)	(0.00)
	{0.000}	{0.000}	{0.000}	{0.046}	{0.312}	{0.216}	{0.594}	{0.847}
Observations	4,187	1,860	1,860	1,292	1,292	1,860	1,859	1,348
Mean (non-eligible)	0.01	0.02	0.01	0.60	31.14	0.54	0.39	0.00
Mean (eligible)	2.18	2.33	0.63	0.67	31.35	0.57	0.36	0.00
Panel B: Males								
Above credit eligibility threshold	1.85	2.32	0.49	-0.04	-4.48	0.15	-0.04	0.00
	(0.24)	(0.40)	(0.13)	(0.08)	(8.65)	(0.06)	(0.06)	(0.00)
	{0.000}	{0.000}	{0.000}	{0.629}	{0.605}	{0.009}	{0.501}	{0.498}
P-value Females=Males	0.555	0.463	0.984	0.070	0.264	0.396	0.399	0.960
Observations	6,473	2,122	2,122	1,553	1,553	2,122	2,119	1,454
Mean (non-eligible)	0.01	0.02	0.01	0.57	28.26	0.55	0.36	0.00
Mean (eligible)	2.15	2.59	0.62	0.67	28.66	0.63	0.32	0.00

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 **??** 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 C2: 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
Finlit vs. Salience	0.131	0.112	0.316	0.196	-0.009	0.006	0.037	-0.034
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	.9360000000000001	2.837	.07	.146
Finlit vs. Salience	0.130	0.086	0.157	0.212	0.007	0.023	0.043	-0.035
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 A1 notes. In columns 3 to 6, regression include controls listed in Table A4 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 D: 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 D1: 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 D1: 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 D1: 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 D1: 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 D1: 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 D2: 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.