The Impact of Digital Credit in Developing Economies: A Review of Recent Evidence*

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Abstract

In recent years, a new generation of "digital credit" products have transformed the consumer lending landscape in many low- and middle-income countries. Offering short-term, high-interest loans via mobile phones or other digital platforms, these products have become wildly popular. This article reviews the small but emerging evidence on the welfare impacts of digital credit. These studies document very high rates of takeup – well in excess of traditional microcredit – despite the fact that customers often do not understand the terms of their loans. Overall, there is little evidence that access to credit has consistent positive impacts on borrower welfare, though two impact evaluations document positive effects on resilience and subjective well-being, respectively. No study finds statistically significant negative impacts of digital credit.

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1 Introduction

Over the past 10 years, digital credit has exploded in popularity across the world. Digital loans are disbursed and repaid electronically, and are often distinguished from conventional credit for being "instant, automated and remote" (Chen and Mazer 2016). That is, digital loans do not require in-person interaction, lending decisions are made by algorithms, and loans are disbursed immediately. Digital credit is also distinguished by the use of "non-traditional data" for credit scoring, such as data on past utility bill payments or information about how the loan applicant uses their mobile phone.

Digital credit has taken different forms in different parts of the world. For example, in China, tech giants like Alibaba and Tencent partner with dozens of small, regional commercial lenders to make unsecured loans (usually via smartphone app) to individuals and small businesses. Only several years after launch, such digital credit products now account for about 5% of China's total unsecured consumer loan market (McKinsey & Company 2021). In Sub-Saharan Africa, which is the site of several of the main impact evaluations discussed in this report, digital credit has also expanded dramatically, but primarily via bank-telco partnerships that leverage existing well-developed mobile money infrastructure. For example, M-Shwari, arguably the best known and most prominent telco digital credit product in the world and a partnership between Safaricom and the Commercial Bank of Africa, reports having 4 million monthly active users in 2020-21 and making about 17 million loans (Safaricom 2021). Microsave Consulting (2019) reports that in 2018 there were 10 digital loans for every traditional loan in Kenya.

Table 1 provides a snapshot of several of the bigger products available at the time of writing, organized by the type of lending model used. For each lender, we show the average loan size, the loan term length, the interest rate or facilitation fee, and the estimated subscriber base. Panel A shows bank-telco partnerships, with two examples: M-Shwari in Kenya and M-Pawa in Tanzania. These loans are offered on the mobile money platform of Safaricom (M-Shwari) and Vodacom (M-Pawa), and feature small loans (the average loan size on M-Shwari is about $40-50 (Safaricom 2021). The facilitation fee on M-Shwari is 7.5% per month, which compounds for at least one more month in the case of late payment;

the rate on M-Pawa is similar. Annualized, these rates are well over 100% APR. Panel B shows a few examples of bank-fintech partnerships, including prominent examples such as Tencent's WeBank in China, KakaoBank in South Korea, and Facio in Brazil. These products offer much larger loans, especially in the two Asian countries. Finally, Panel C shows some examples of digital loans offered by fintech firms that are financed by investors without the intermediation of a bank. Major players include Branch and Tala, which are providing unsecured consumer loans via their smartphone lending apps across multiple developing countries. Interest rates and terms vary considerably on these lending apps, but generally feature high rates as well.

These lenders have reached a substantial number of borrowers already. M-Shwari reports having roughly 4 million active monthly borrowers, while M-Pawa reports having 8.5 million. WeBank reports 28 million users as of 2019, KakaoBank 14 million, and Facio 7 million. Branch has 4 million users, and Tala 6 million.

While millions of loans have been made, little is known about the impact of the loans on borrowers. The impact is not obvious. On the one hand, a vast body of research has shown that credit and liquidity constraints can have important welfare consequences in developing economies, and so access to highly liquid digital loans with minimal transaction costs could, in principle, provide real benefits to borrowers. And indeed, the sheer volume of loans is indicative of unmet demand for credit.

Table 1: Sample of Digital Credit Products

Product (country)	(1) Loan size	(2) Loan term length	(3) Interest/Fee	(4) Subscriber base
Panel A. Bank-MNO partnerships				
M-Shwari (Kenya)	\$1-100	up to 30 days	facilitation fee: 7.5% (per month)	4M monthly active users; 17M loans (2020)
M-Pawa (Tanzania)	\$0.5-200	up to 30 days	facilitation fee: 9% (per month)	8.5M users (2019)
Panel B. Bank-Fintech partnerships				
WeBank (China)	\$70-44,000	up to 20 months	avg. 18% (APR)	28M users; 460M loans; \$579M disbursed (2015-2019)
KakaoBank (South Korea)	up to ∼\$25,000	up to 1 year	1.2-14.5% (APR)	14M users (2021). ∼ \$1.5B unsecured loans (2020)
Facio (Brazil)	up to 30% of borrower's net salary	1 month (until next month's paydate)	flat fee: 1.9%	7M loans
Panel C. Non-bank-financed Fintech				
Branch (Kenya, India, Nigeria, Tanzania)	\$2.2-1,200	1-12 months	1.5-25% (monthly)	4M users, 21M loans; \$600M disbursed (2021)
Tala (Kenya, Philippines, Mexico, India)	\$10-500	21-90 days	facilitation fee: 5-15%. extension fee: 8%	6M users; \$2.7B disbursed (2021)

Notes: Monetary values converted into USD.

On the other hand, easy access to high-interest loans does not necessarily benefit consumers. Many borrowers are poorly informed about loan terms: for instance, Brailovskaya et al. (2021) find that only one third of potential borrowers in Malawi know the interest rate, the due date, or are even aware of the existence of late fees. Loan terms are often not communicated clearly to borrowers (Garz et al. 2021), and it may be in the lender's best interest to keep terms opaque. Many borrowers pay late, incurring sometimes sizeable fees (for example, in Malawi, the late fee for the digital credit product Kutchova is 12.5%, assessed multiple times). Others default, losing access to future loans and potentially being reported to credit bureaus.[1] Anecdotally, there are a number of news media articles about negative effects of digital credit.[2]

In this paper, we review the small but emerging evidence base on digital credit, focusing on 8 completed studies. These studies were conducted in six countries: four in Africa (Kenya, Malawi, Nigeria and Ghana) and two in Latin America (Haiti and Mexico). Three of the products are MNO-bank partnerships, two are MNO airtime loans, and the other three are non-bank lenders. Studies differ in product design and target populations as well: seven are short-term loans suited for immediate liquidity needs (or airtime), while one is targeted towards farmers with longer repayment periods. On the whole, the customer bases for these products tend to include relatively more affluent borrowers, sometimes mechanically through the requirement of owning a smartphone. Customers tend to be younger and more educated than average.

We draw three main lessons from this set of studies. First, there exists robust demand for the products. Of those studies targeting a representative sample of eligible borrowers, the take-up rate ranges from about 34% to 70% (with one exception that is lower). Both studies of telco-MNO products have takeup rates around 35%. This take-up level is on the high end documented in most studies of traditional microcredit (e.g., Banerjee et al. 2015). Digital credit is especially notable because the population of eligible borrowers is likely much larger than for traditional credit (potentially including anyone with a phone). On the other hand, the value of loans is much lower than traditional microcredit: many loans are as small as a few dollars, whereas the average size of microcredit loans in Banerjee et al. (2015) was hundreds or thousands of dollars.

Our second finding comes from a very small set of studies which measured the welfare impacts of digital credit. We note that of the 8 original studies, several were beset by implementation and logistical challenges with the lender or product – a common occurrence with collaborations between researchers and digital credit providers, since lenders frequently change plans or remove products from the market. We thus focus on 3 main studies that have rigorous results on welfare impacts: Suri et al. (2021), Björkegren et al. (2021), and

[1]Reports indicate that millions of people in countries like Kenya have been reported to the credit reference bureau. See Johnen et al. (2021) for more detail.
[2]See Brailovskaya et al. (2021) for several examples.

Brailovskaya et al. (2021). On the whole, these three studies show generally modest effects, though the sign on several indicators is positive. Suri et al. (2021) studies M-Shwari in Kenya, and finds that the product helps households to cope with unexpected income shocks. The paper finds no evidence of harmful effects on other outcomes. Björkegren et al. (2021) looks at a digital smartphone lending app in Nigeria, finding positive effects on subjective well-being, but statistically insignificant effects on other measures of welfare. Brailovskaya et al. (2021), which studies the Kutchova product in Malawi, shows similar, modest effects on most outcomes. While these modest effects are perhaps unsurprising given the small loan sizes, they do suggest that the worst fears of digital credit have not been realized. However, there is no evidence of transformative positive effects.

At the same time, several of the studies we review highlight areas of concern. For example, Brailovskaya et al. (2021) document that borrowers are poorly informed about even the basics of loan terms, such as the existence of a late fee. Moreover, the lender in that study changed loan terms without informing customers. Similar findings have been shown in other reviews Ogada and Hammond 2021. In an environment with intense demand for even high-interest loans, but poorly informed customers, there is opportunity for abuse. Interventions to address these consumer protection issues (such as those being evaluated by the IPA Consumer Protection Initiative) are sorely needed. For instance, through a randomized controlled trial, Brailovskaya et al. (2021) found, surprisingly, that increasing financial literacy actually increased loan demand – as well as loan repayment. More studies of this kind are needed.

Another important finding is Burlando et al. (2021), which shows that exogenous increases in waiting times increase loan repayment, suggesting that digital credit might be "too fast." While the authors are not able to definitively attribute this finding to a specific channel, it does suggest that changes in product design – in this case, by adding mandatory waiting periods – could be beneficial.

Overall, this review suggests that digital credit – even offered at very high interest rates – may benefit some customers. While results indicate that the positive impacts are quite modest for the average consumer, the fact that people are so eager to take out these loans suggests unmet demand, and implies that people value access to these products. However, we caution that this evidence base is small and covers only a few products. The digital loans that were studied were offered by major providers, and so might be more trustworthy than other lending apps (though even in this set, at least one of the lenders changed late fees without disclosure). In the wider world, the opportunity for scams is clear, and fraudulent lending apps abound (Fu and Mishral 2021): consumers are desperate for loans, even at high rates, and are often taking out loans without knowing the terms.

The remainder of this article proceeds as follows. Section 2 describes the set of products studied and the methodologies used. Section 3 describes results. Section 4 discusses open questions for further research. Section 5 concludes.

2 Studies included in this review

We include 8 studies in this review, 7 of which were funded by the Digital Credit Observatory at the Center for Effective Global Action (CEGA). We split the studies by the type of lender: Bank-MNO partnerships (Suri et al. 2021, Brailovskaya et al. 2021 and Toth 2021), airtime loans (Barriga-Cabanillas and Lybbert 2021 and Shema 2021), and non-bank fintech products (Björkegren et al. 2021, Burlando et al. 2021 and Karlan et al. 2020). These studies and products are summarized in Table 2.

Table 2: Digital Credit Products Included in Review

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bank-MNO Partnership			Airtime Loans		Non-bank Credit		
	Suri et al. (Kenya)	Brailovskaya et al. (Malawi)	Toth (Myanmar)	Barriga-Cabanillas and Lybbert (Haiti)	Shema (anonymous E. African country)	Björkegren et al. (Nigeria	Burlando et al. (Mexico)	Karlan et al. (Ghana)
Panel A. Basic information								
Product name	M-Shwari	Kutchova	(anonymity requested)	(anonymity requested)	(anonymity requested)	Branch	(anonymity requested)	Mergdata Digital Finance Module
Payment platform	Safaricom (telco)	Airtel (telco)	mobile app	(anonymous MNO)	(anonymous MNO)	mobile app	N/A	mobile app
Creditor	Commercial Bank of Africa (CBA)	FDH Bank	(anon. commercial bank)	(anonymous MNO)	(anon. independent lender)	(proprietary funds)	(anon. fintech company)	Farmerline
Product launch date	2012	2016	2018	2018	(anonymity requested)	2017	2018	2018
Customer base	4.5M active users; 10M accounts	~27K eligible borrowers	~65K agents (universe)	~95% of customer base	46% of MNO subscriber base	4M users		500,000 farmers (across 13 countries)
Clientele	mobile money users	mobile money users	mobile money agents	pre-paid cellphone subscribers	MNO subscribers	smartphone owners	consumers with mobile phone, formal employment and bank account	smallholder farmers
Data used for scoring	mobile money usage	mobile money usage	monthly mobile money transaction volume	N/A(automatically eligible 4 weeks after activating account)	previous airtime recharge amounts	proprietary credit score	credit and repayment history, nontraditional credit score	data on crop production
Loan term length	30 days	15 days	1-12 months	30 days	7 days	1-28 days	7-30 days	6 months
Loan size (USD)	\$1-100	\$1.4-14	\$70-3,500	\$0.13-2 (airtime)	\$0.02-0.32	\$2.6-528	\$75-150	~40
Panel B. Fees and interest								
Fees	facilitation fee: 7.5% (per month)	facilitation fee: 10% (for first 15d)	16% APR	~11% per loan	15-75% (for 7d)	1.5-20% monthly interest	16% monthly interest	4% per month (starting from 3m after loan)
Late penalties	30d extension (7.5% fee); reported to credit bureau if not repaid within 120d	12.5% fee for every 15d late (max. of 3 times)	no late fee; ineligible for future loans	no late fee; auto-repay from recharges; phone number deactivated for default	no late fee; auto-repay from recharges; phone number deactivated for default	no late fee; ineligible for future loans	1.5% for each day of delay	no late fee; ineligible for future loans

2.1 Bank-MNO partnerships

The first two studies (in the first two columns of Table 2) focus on loans backed by commercial banks, where transactions occur using mobile money: Suri et al. (2021) study M-Shwari, which is offered by Safaricom in Kenya; Brailovskaya et al. (2021) study Kutchova, which is offered by Airtel Malawi. M-Shwari is far more developed than Kutchova, with 4.5 million users, compared to less than 30,000 on Kutchova. Both use mobile money transaction records to construct a credit score and determine loan eligibility, and both feature short repayment terms at high interest rates. M-Shwari charges 7.5% for a 30 day loan, while Kutchova is 10% over just 15 days. Both feature large late payment fees, making the nominal rate extremely high when loans are repaid late (see Brailovskaya et al. (2021) for a more detailed discussion). Loan sizes are small, especially on Kutchova. Kutchova also institutes auto-repayment for late loans (i.e. deducting repayment directly from a mobile money account, and charging fees on this sum).

Toth (2021), highlighted in the third column, studies a product in Myanmar which targets mobile money agents, rather than consumers. Because these agents are vetted by the network and hold cash in e-float, they are less risky. Consequently, loan sizes are as large as thousands of dollars, and interest rates are 16% APR.

2.2 Airtime loans

Columns 4 and 5 of Table 2 provide details on two products that provide 'airtime' loans, which allow customers to borrow the credit needed to use traditional mobile services (such as making calls and sending text messages). Barriga-Cabanillas and Lybbert (2021) study an airtime loan product in Haiti that is backed by the phone company. Rates are similar to the other products (11% per loan, due in 30 days, with automatic repayment from future airtime recharges). Shema (2021) studies micro-airtime loans in an East African country. The interest rates on these loans are similarly exorbitant: 15-75% for even 7 days.

2.3 Non-bank digital credit

The final columns of Table 2 highlight three studies of fintech products. Björkegren et al. (2021) evaluate a popular smartphone-based lending product in Nigeria, which offers 1-28 day loans at interest rates of 1.5-20% per month. Burlando et al. (2021) study a web-based digital loan in Mexico, where loans are due in 7-30 days and interest rates are as high as 478% (APR). Finally, Karlan et al. (2020) study a product targeted at farmers in Ghana called the Mergdata Digital Finance Module. These loans differ from others in that they are for 6 months and are for slightly larger sums (an average of $40), and with a lower interest rate of 4% per month.

2.4 Study designs

Table A1 provides an overview of the research methods used by the eight studies covered in this review, including the identification strategy, sample size, and timeline. Of the studies with detailed impact results, two are regression discontinuities (Suri et al. 2021 and Brailovskaya et al. 2021) and one is an RCT (Björkegren et al. 2021).

3 Results

3.1 Borrower characteristics in study samples

Table 3 presents basic statistics on the subject populations covered by these studies, focusing on a few variables that were common to most of the studies.[3] While access to finance is lower for women worldwide (Demirgüç-Kunt et al. 2018), several studies stratified on gender and consequently the gender ratio is closer to parity in many studies. The percent female ranges from 24-56%. In all studies, the study sample is relatively young: the average age is typically between 30 and 40, with the exception of the product targeting farmers (Karlan et al. (2020)). These samples include both urban and rural households: the percent urban ranges from 23-71%.

[3] Shema (2021) is dropped from this and subsequent tables because the study contains no data on borrower characteristics.

The final two rows describe the education and income of the study populations. These samples are much better educated than national averages, with the average education ranging from 10.8-14.2 years. By contrast, the average years of education is 6.6 in Kenya, 4.7 in Malawi, 5.0 in Myanmar, and 6.7 in Nigeria.[4] As expected, measures of income and expenditures suggest these populations are much better off than average. Annualized yearly income or expenditures is $2,100 in Suri et al. (2021), $2,500 in Brailovskaya et al. (2021), and $1,600-$3,300 in Björkegren et al. (2021). The figure is much higher among mobile money agents in Myanmar (over $12,000). By contrast, GDP per capita in 2020 is about $1,832 in Kenya, $625 in Malawi, $2,097 in Nigeria and $1,400 in Myanmar.[5] Even one of the farming studies shows crop sales of over $1,300, well above sales of typical subsistence farmers. The one outlier here is Burlando et al. (2021), which reports an average income of only $1,200 in Mexico, a country where GDP per capita is far higher than these other contexts.[6]

[4]Statistics from the United Nations Human Development Reports.
[5]Source: World Bank.
[6]Mexico's GDP per capita was $8,348 in 2020, according to World Bank.

Table 3: Study Sample Summary Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Bank-MNO Partnership			Airtime	Non-bank		
	Suri et al. (Kenya)	Brailovskaya et al. (Malawi)	Toth (Myanmar)	Barriga-Cabanillas and Lybbert (Haiti)	Björkegren et al. (Nigeria	Burlando et al. (Mexico)	Karlan et al. (Ghana)
Female	0.52	0.47	0.56	0.45	0.24	0.44	0.27
Age	30.5	35.1	37.6	31.6	30	37.5	51
Urban	-	0.58	0.23	0.71	0.33	-	0.17
Years of education	10.8	11.6	13	-	14.2	-	7.3
Expenditure/income (USD, annualized)	$2,140 (expend.)	$2,460 (expend.)	$12,250 (income)	-	Median income bracket: $1,600-$3,300	$1,170 (income)	$1,300 (crop sales)

Notes: All monetary values in USD.

3.2 Takeup and Repayment

Table 4 shows statistics on loan take-up and repayment for these eight studies. Take-up rates in the two studies of MNO-bank loans are reasonably high: 34% (over 18 months) around the scoring threshold in Suri et al. (2021) and 35% (over 11 months) in Brailovskaya et al. (2021). One difference in these two studies, however, is that in the first study, 30% of the group below the threshold had an M-Shwari loan. In the second study, the digital product was new and so nobody below the threshold had a loan. The average loan size is small in both studies, especially in Malawi ($2.8 in Kenya and $1.25 in Malawi). The total amount of credit over the study period was about $25 in Kenya but only $2 in Malawi. Because the (regression-adjusted) first stage was about 24 percentage points and $10 in Kenya and 35 percentage points and $1.70 in Malawi, this implies that the increase in credit for those induced to borrow from becoming eligible was about $42 in Kenya and only $6 in Malawi. The default rate for loans was about 7% in Kenya and 15% in Malawi (in Malawi, of those not paying back, 11% fully defaulted). This higher default rate may be attributable to the newness of the product. This is a major reason for the enormous late fees on Kutchova: with high default rates, these fees help keep the product solvent.

Column 3 shows data on loans to mobile money agents. These loans are likely far less risky and better targeted, since the MNO has an ongoing relationship with the agent, and has lots of data on the agent's solvency. Agents also face a steady stream of customers and so should likely have liquidity to pay back loans. Surprisingly, though, only 12% of agents took up these loans (although those who took them up took out large sums of money, a total of over $2,000). As expected, default is close to zero.

Columns 4-5 present studies about airtime loans. The take-up for both products is very high: about 45% over 8 months in an anonymous East Africa country (Shema 2021), and 70% over 11 months in Haiti (Barriga-Cabanillas and Lybbert 2021). These loans are for very small sums (average loan size of $0.11-0.55). The airtime loans can be automatically collected in subsequent airtime recharges, and default occurs only in 2-3% of cases.

Columns 6-8 show non-bank products. For all of these products, take-up rates are very high, though this is not necessarily that informative because the studies were designed around interested borrowers. For example, Björkegren et al. (2021) focused on people who had recently installed the lending app on their phone; Burlando et al. (2021) are only able to study borrowers who had already been approved for loans; and Karlan et al. (2020) focus on farmers who have already qualified for a loan. The average loan size in these studies is $15 in Björkegren et al. (2021), $40 in Karlan et al. (2020) and $91 in Burlando et al. (2021). Default rates also vary widely. In the sample of loans observed in Björkegren et al. (2021), the default rate is 7%, close to that of the MNO-bank lenders. This is interesting since there are no late fees on this product, but may be due to the size of the initial loan. By contrast, the online loans offered in Burlando et al. (2021) are far riskier and feature a default rate of 27%. It is perhaps not surprising, then, that the lender has since stopped offering this product.[7]

[7] Karlan et al. (2020) do not have data on default at the time of this writing.

Table 4: Take-up

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bank-MNO Partnership			Airtime Loans		Non-bank Credit		
	Suri et al. (Kenya)	Brailovskaya et al. (Malawi)	Toth (Myanmar)	Barriga-Cabanillas and Lybbert (Haiti)	Shema (anonymous E. African country)	Björkegren et al. (Nigeria)	Burlando et al. (Mexico)	Karlan et al. (Ghana)
Time period over which outcomes measured	18 months	11 months	13 months	11 months	8 months	3 months	7 months	6 months (loan term)
Take up rate	34%	35%	12%	70%	45%	85%	-	60%
Average loan size (USD)	$2.8	$1.25	$1,166	$0.50	$0.11	$15	$91	$40
Total value of loans (USD)	$25	$2	$2,200	$2	$13	$56	N/A (no borrower ID in data)	$40 (one-time loan)
Default rate	7%	15% (11% zero repayment)	0.7%	<2%	2-3%	7%	27%	-

Notes: All monetary values in USD. Studies differ in their period over which outcomes were measured, so are not directly comparable – see first row. We do not report take-up for Burlando et al. (2021) because their sample is restricted to people approved for loans.

3.3 Impacts

Evidence on the welfare impacts of digital credit

To this point, our review has discussed 8 different studies of digital credit. To synthesize evidence on the welfare impacts of digital credit, we focus on our discussion on the 3 studies with extensive follow-up data and random or quasi-random variation in access to credit: Suri et al. (2021), Björkegren et al. (2021), and Brailovskaya et al. (2021). When available, we also discuss results from other papers.

In their regression discontinuity of M-Shwari in Kenya, Suri et al. (2021) find that crossing the score threshold increases the probability of taking a loan by 24 percentage points, on a base around 40%, and increases the total amount of credit by about \$10, on a base of \$15. The effect on *any* source of loan is smaller (10 percentage points), suggesting that M-Shwari crowds out other sources of credit to some extent. Nevertheless, getting access to M-Shwari increases total credit usage.

The authors utilize their household data to examine the impact of unexpected shocks on consumption. Shocks are extremely common: 89% of households below the threshold reported a shock in the 6 months prior to the survey.[8] Conditional on having a shock, the authors document that 68% of households reduce expenses. Digging into details, about 45% reduce food spending and, surprisingly, 30% reduce medical spending (this is surprising since some of the shocks are health-related).

The main finding in Suri et al. (2021) is that people just over the threshold – and therefore loan-eligible – are 6.3 percentage points less likely to forego an expense (significant at 5%), 4.5 percentage points less likely to forego a food expense (insignificant), and 4.9 percentage points less likely to forego a medical expense (significant at 5%). Finally, the authors look at a number of other outcomes, including expenditures, savings, and assets, and find no evidence of impacts on these outcomes. Thus, this study shows a positive but somewhat modest effect on risk-coping (since over 61% of people with access to M-Shwari still had to reduce expenditures even with access) but no effect on other outcomes.

[8] Shocks include the death or illness of a household member, accidental injury, loss of employment, violent injury, the failure or loss of a business, livestock death, crop disease or pests, theft/robbery/burglary/assault, fire or house destruction or damage, and experiencing a drought or flood.

A second study that documents impacts is Brailovskaya et al. (2021), which has 2 parts: an RD around a scoring threshold for newly eligible borrowers, and a financial literacy RCT. In the regression discontinuity, the authors examine the effect of digital credit loans (which were in this case for small sums, just \$1.4) on outcomes such as self-reported financial security, savings, and self-reported ability to cope with shocks. The authors find small but positive point estimates on outcomes like financial security, but unlike Suri et al. (2021) find no evidence that the loans were used for risk-coping.

The third study by Björkegren et al. (2021) studies the impact of access to digital credit loans from Branch in Nigeria. The research design used a randomized control trial with two arms: The first varied whether people would be offered *any* loan, by randomly dropping the minimum credit score requirement for some new loan applicants; the second randomly varied the *size* of the initial loan offered to new loan applicants, with values ranging from NGN 1000 to NGN 13,000 (roughly USD\$3 to \$36). The authors then conducted follow-up phone interviews with 1,618 study participants roughly 3 months after the first loans were issued.

As with the other two studies, Björkegren et al. (2021) find that the randomized treatments significantly increased the amount of money that customers borrowed from the lender; conversely, there was a modest drop in the amount borrowed from informal sources (such as friends and family). The increased access to credit also led to an overall increase in financial health, based on a standardized 14-question financial health index.

The effects on well-being were more ambiguous. Following a pre-registered pre-analysis plan, the authors analyzed impacts along several different dimensions of welfare, but found little evidence of significant positive or negative impacts of loan impacts. The one exception was with measures of subjective well-being, where the study found that increased access to digital credit led to a significant ($p < 0.01$) improvement in subjective well-being, primarily through increases in mental health, measured using the standard Patient Health Questionnaire (PHQ-9) survey module.

Differential impacts by gender

A vast literature demonstrates large gender disparities in access to finance in developing countries (e.g., Demirgüç-Kunt et al. 2018). For example, in Brailovskaya et al. (2021), about 60% of the mobile money network is male, and this is even more biased in regards to access to credit (since men use mobile money more than women). Digital technologies have traditionally been thought of as likely to reduce gender inequities, since they are "gender-blind." However, a robust literature now documents the biases that exist in algorithmic decisionmaking, and in particular, the difficulty of achieving fairness without awareness Dwork et al. 2012; Barocas et al. 2018.

Several of these studies were stratified by gender. In this set of studies, however, there is limited evidence of gender differences. For example, Brailovskaya et al. (2021) and Björkegren et al. (2021) find no evidence of differential effects by gender. However, there is likely to be some form of heterogeneity based even on the baseline difference in access.

Other impacts

Several other studies show impacts on other margins. Burlando et al. (2021) examine the effect of waiting time on default, using quasi-random variation in loan approval times (based on the batching of the processing of loan applications). Interestingly, they find that increasing waiting times improves repayment: roughly doubling the waiting time decreases the default rate by 21%. While the authors do not have data to document the cost of this waiting time, their result raises the possibility that credit might be "too fast" in some cases. They argue that digital credit may be more effective if consumers were required to wait for some amount of time.

Shema (2021) conducts an experiment in which credit limits for small airtime loans were randomized. He finds that people with higher limits take out more credit, but that they are more likely to default. The effects are substantial: doubling the credit limit raises the probability of default by about 14 percentage points.

Finally, Barriga-Cabanillas and Lybbert (2021) conduct an event study analysis to examine the effect of airtime loans on airtime usage in Haiti. They find that increased access to credit increases usage of airtime.

4 Discussion

4.1 Customer Knowledge and Consumer Protection

These preliminary studies show some modest positive effects of digital credit, and do not document any cases of large negative effects. However, it is clear from these studies – and especially from a broader set of qualitative observations – that there are still reasons to be concerned about the lack of consumer protections in the burgeoning digital credit ecosystem.

Within the impact evaluations discussed above, the main piece of evidence comes from the financial literacy RCT in Brailovskaya et al. (2021). In the study, the authors ask questions of borrowers about basic knowledge of loan terms, yet document that most borrowers are uninformed. For example, only about one third of borrowers could recall the interest rate, knew the due date, or were even aware that there are late fees. While the Kutchova system does provide some reminders on these items for borrowers after the loan has been disbursed (i.e., loan repayment reminders and a reminder of the amount paid), this baseline lack of knowledge means that borrowers may be taking out loans without full information. The RCT was designed to provide this information, but also discuss the costs of failing to repay on time. In particular, eligible borrowers took an interactive voice response (IVR) financial literacy module. The module discusses the sizeable fees to borrowers and the risks of default (including reporting to the credit bureau), and suggests using savings instead.

Surprising to the researchers, the intervention *increased* loan demand.[9] In this context, researchers interpret this result as showing that, even though borrowers are not informed, the loan terms compare favorably to other options. For example, they document that the interest rates on other lending options, such as Village Savings and Loan Associations, are also very high. In follow-ups, many respondents reported that the intervention made them *more* interested in a loan.

The intervention also caused borrowers to be less likely to default. This result suggests that information disclosure could potentially actually be profitable in this context – which is ironic given that loan terms, and in particular late fees, are not clearly disclosed by the

[9]This result is in contrast to a prior intervention which inspired the RCT, Bertrand and Morse (2011), in which borrowers from a payday lender were informed of loan terms, and choose to reduce their demand for such loans.

lender (Brailovskaya et al. 2021). Shrouded or hidden fees are also common in lenders across the world.[10]

The need for consumer protections in lending markets is not unique to low- and middle-income countries, and there has been vocal critique of payday loans and other products offered in other global markets (c.f. Morse 2011; Skiba and Tobacman 2019). However, the rapid growth of digital credit is particularly concerning, given the lack of regulation in many of these new markets (Garz et al. 2021). It is also important to note that the studies we review are of larger products offered by prominent digital lenders; with smaller, lesser-known products, the potential for scams and fraud is much greater (Fu and Mishral 2021).

4.2 Product Innovation

Another issue about the current generation of digital credit is that most consumer loan products offer only small, high-interest, short-term loans. There is substantial scope for product innovation to increase the range of benefits available to consumers. The current set of products can be useful to cope with times where money is badly needed, but are generally too small to allow for productive investment, which is where credit might have the biggest welfare impacts. Credit constraints may prevent high-return investments in human capital (i.e. Duflo et al. 2021 for scholarships for secondary school in Ghana), business investment (i.e. de Mel et al. 2008), or in agriculture. These loans only pay off in the future, and also involve larger sums, and so may be less in need of being "instant, automated, and remote." Still, expanding credit to these populations (via for example the use of nontraditional data) could be beneficial.

It remains to be seen whether digital credit can fill this gap. We are not aware of any completed studies of digital credit for productive investment. Karlan et al. (2020) is one example, but issues with the lender have limited their ability to complete the planned impact evaluation. There are a few products that are coming on line geared specifically at farmers.[11]

There are also several products that use digital credit in innovative ways. For example,

[10] See Garz et al. (2021) for a discussion.

[11] For example, Safaricom is offering a product called DigiFarm, targeting farmers.

digital technology allows the use of “digital collateral,” for instance by using lockout technology that allows for a product to be remotely deactivated. This allows a lender to provide the product on credit, and then deactivate the product if the borrower does not repay. This technology has been used extensively with solar panels by companies such as M-Kopa and Fenix. This technology has proven effective in increasing purchase in a few recent RCTs (e.g., Gertler et al. 2021, Francis 2018). M-Kopa and other firms are also expanding into other products, such as home appliances.

Ongoing work also explores the potential for innovative uses of the data generated by digital credit customers. For instance, Rolf et al. (2020) develop a theoretical framework that demonstrates how lenders might jointly optimize for private and public objectives – such as the lender’s desire to maximize profits and the borrower’s (or regulator’s) desire to maximize the welfare of the consumer. In principle, the same “big” data used to credit score a consumer (Björkegren and Grissen 2017) could be used to help lenders estimate and prioritize the likely welfare impacts of lending to that consumer.

A final promising area of ongoing research asks whether loan products can be better optimized to serve women, and improve women’s economic empowerment. For instance, an ongoing study in the Dominican Republic by Blumenstock et al. (2021) is testing whether gender-differentiated credit scores – which use different credit scoring algorithms to score women and men – can increase credit access to women without sacrificing profitability. While the study is still in the field, preliminary results suggest that as much as 80 percent of women would receive a higher credit scores using the gender-differentiated approach than they would with a traditional model.[12]

5 Conclusion

The global expansion of digital credit is providing millions of historically unbanked individuals with access to formal loans for the first time. On the one hand, we might hope that this transformation could empower populations to make productive investments, smooth

[12]For more detail, see https://financialallianceforwomen.org/news-events/gender-differentiated-credit-scoring-a-potential-game-changer-for-women/.

consumption in the face of income volatility, and otherwise have more autonomy over their financial decisions. On the other, the high interest rates and opaque loan terms could lead to systematic over-indebtedness and create financial distress.

This survey of preliminary evidence suggests that the average welfare impacts of digital credit are, to date, neither very positive nor very negative. The majority of studies find no significant impacts on the majority of measures of consumer welfare. There is some evidence that digital credit may lead to modest improvements in consumer resilience and subjective well-being, but those findings have not yet been replicated across multiple contexts. We interpret this as evidence that while digital credit may be transforming the consumer lending ecosystem, it is not transforming the lives of the borrowers.

Yet the current state of digital credit products and (lack of) regulation highlights several areas of concern. In particular, there is a clear lack of understanding among borrowers of the terms of the loans they are using, or of the consequences of default or late repayment. The current evidence base of impact evaluations is also very thin, based on only a handful of products evaluated in specific markets. The lack of robust evidence highlights the need for concerted and coordinated future work to better understand the welfare impacts of digital credit.

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Table A1: Study Information

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bank-MNO Partnership			Airtime Loans		Non-bank Credit		
	Suri et al. (Kenya)	Brailovskaya et al. (Malawi)	Toth (Myanmar)	Barriga-Cabanillas and Lybbert (Haiti)	Shema (anonymous E. African country)	Björkegren et al. (Nigeria)	Burlando et al. (Mexico)	Karlan et al. (Ghana)
Panel A. Research design								
Study design	Regression discontinuity	Regression discontinuity	Regression discontinuity, Difference in differences	Event study	RCT	RCT	Regression discontinuity	RCT
Identification	around initial credit score cutoff	around credit score cutoff	policy change	change in loan eligibility status	randomized at customer level	randomized at customer level	around cutoff for loan disburse batches (3-4/day)	randomized at individual farmer level
Sample size	6,000	7,034	5,400	96,342	50,000	1,618	8,371	1,377
Intervention	digital credit loan offer	digital credit loan offer	policy change in loan offer amount	airtime loan offer	credit limit change	digital credit loan offer	late disbursement of approved loan	digital offer of farm inputs on credit
Panel B. Study timeline								
Credit offering	Jan - Mar 2015(account opening)	Jul 2019	Mar 2019	May - Jul 2019	Aug 2019 - Mar 2020	Aug 2019 - Feb 2020	Nov 2018 - May 2019	
Impact Surveys	Sep 2016 - Jan 2017	late 2019-early 2020	phone surveys: Oct 2020 - Mar 2021	Admin data only	Admin data only	Nov 2019 - Feb 2020	Admin data only	

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