

Digital Credit: A Snapshot of the Current Landscape and Open Research Questions*

Eilin Francis[†]

Joshua Blumenstock[‡]

Jonathan Robinson[§]

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1 Introduction

Lack of access to finance is suspected to be an important impediment to development in low-income countries. Some symptoms consistent with binding liquidity constraints include high marginal returns to capital,¹ difficulty coping with unexpected income shocks such as household illness,² and a response of investment in durable goods such as bednets or water connections in response to credit (Tarozzi et al. 2013; Devoto et al. 2011). While these stylized facts suggest unmet demand for credit, take-up of microfinance has been rather low in experimental trials and impacts have been modest (Banerjee et al. 2015). This has led some observers to question whether microfinance is a valuable development program, or whether resources should be put elsewhere.

A plausible reason that microcredit has been disappointing is that the existing set of credit products might not be appropriate for target customers. For example, many microcredit products still involve large transaction costs (such as travel costs to the nearest bank branch or time costs in regular group meetings), have imposing loan terms, or significantly restrict how loans can be used.

In the past few years, *digital credit* has emerged as an alternative mechanism for providing short-term loans. In a typical digital credit offering, a mobile phone operator will partner with a financial institution to provide small, short-term loans directly to customers over an existing mobile money ecosystem (we discuss other models of digital credit later). This approach offers several advantages to existing microcredit or bank credit. First, digital credit has the potential to dramatically lower transaction costs, since loans can be disbursed through mobile money, and converted to cash through existing agent networks (which are typically far more extensive than bank or ATM networks). Second, loans can be disbursed immediately, without requiring in-person

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[†]University of California, Santa Cruz, email: elfranci@ucsc.edu

[‡]University of California, Berkeley and CEQA, email: jblumenstock@berkeley.edu

[§]University of California, Santa Cruz and CEQA, email: jmrtwo@ucsc.edu

¹Among others, see de Mel, McKenzie, Woodruff (2008), Udry and Anagol (2006), Banerjee and Duflo (2014) and Fafchamps et al. (2014).

²See, for example, Gertler and Gruber (2002) and Dupas and Robinson (2013). See Dercon (2002) for a review.

vetting by a financial institutions. And third, digital credit providers use nontraditional data (in particular, mobile money and airtime usage) to develop alternative credit scores – which make it possible to extend credit to large groups of individuals without collateral or traditional scores. The result is a product that has been very popular with consumers. For example, 1 in 5 Kenyans (4.5 million people) were using Safaricom’s M-Shwari digital credit product as of 2015 (Cook and McKay, 2015).

At the same time, there are reasons to be concerned with the rapid expansion of digital credit in developing countries. In particular, the effective interest rates charged to consumers are typically quite high - for example, the “facilitation fee” for an M-Shwari loan is 7.5% per month (138% APR), and many products are much more expensive than this. Loans thus tend to look like payday loans in the developed world; while high-interest rate loans can in principle be helpful for liquidity constrained customers by providing cash in times of high need (i.e. Karlan and Zinman 2010; Morse 2011), they may also be harmful, causing overindebtedness and bankruptcy (Skiba and Tobacman 2009), and making it hard to pay bills (Melzer 2011). Moreover, consumer protections for these digital loans is still in its infancy – there exist few protections for borrowers and anecdotal evidence suggests many borrowers do not fully understand loan terms (McKee et al 2015). Default is common enough that an estimated 2 million people have been reported to the Kenyan credit bureau for M-Shwari default, many for sums of a few dollars. It is an open question as to whether consumers are fully informed of the costs of credit, or whether providing more information may reduce demand for these high-interest rate loans (see Bertrand and Morse 2011 for evidence that information reduces payday loan demand in the US).

In this overview, we summarize the current state of digital credit, focusing primarily on the currently dominant form of credit – consumer loans offered through mobile money systems, often backed by a financial institution. In Section 2, we summarize the current landscape. In Section 3, we discuss various ways in which digital credit will represent a change from previously available forms of credit, in particular microcredit or bank loans. Section 4 discusses some possible directions for further research.

2 Background

2.1 What is digital credit?

In 2007, the Kenyan telecom company Safaricom launched M-Pesa, a digital system which allows users to exchange cash for e-currency, which can be stored or sent to other users over the mobile phone network, and then withdrawn from the system through agents (these are often shopkeepers who work as M-Pesa agents in addition to their main business).³ Since 2007, mobile money has rapidly proliferated in the developing world, and today there are more than half a billion registered

³The first mobile money system - Smart Money - was launched in the Philippines by Smart Communications and Banco de Oro (BDO) in 2001.

mobile money accounts across 270 mobile money services in at least 90 countries (GSMA 2016a).⁴ While bank accounts are much more common than mobile money in most of the world, this is not true in Africa – even by 2014, mobile money ownership exceeded bank account ownership in many African countries (and this gap has surely grown by now). The introduction of mobile money has been associated with important welfare effects: in Kenya, mobile money has been linked to improved risk-coping (Jack and Suri 2014) and a reduction in poverty (Jack and Suri 2017). Consequently, many in the policy and aid communities view mobile financial services as the future to improving financial access in poor countries (GSMA 2016a; Lauer and Lyman, 2015).

Though mobile money could in principle have been used for other financial purposes such as savings, many people have primarily used mobile money for person-to-person transfers.⁵ This was due in part to regulatory issues, since telecom providers were not registered as banks and therefore were prevented from earning interest on deposits.⁶ Mobile money providers therefore did not market themselves as banks, and the products were not particularly well suited for saving since they featured withdrawal fees but no interest. In November 2012, Safaricom launched M-Shwari, a collaboration with the Commercial Bank of Africa (CBA), in which users can earn interest on savings and qualify for loans backed by CBA.

M-Shwari has taken off from there:⁷ in the first two years of existence, Safaricom made over 20 million loans to 2.6 million borrowers (Cook and McKay 2015).⁸ In response to this success, similar products have now been launched in many other countries – see Table 2 for a partial listing of products. Though it is difficult to accurately measure global demand for loans, existing evidence suggests substantial consumer interest (Table 2, Column 8 compiles statistics on demand, where available). For instance, M-Pawa in Tanzania reports making loans to 4.9 million borrowers during its first two years (Aglionby, 2016).

Relative to conventional credit, digital credit offers several key differences, of which CGAP (Consultative Group to Assist the Poor - a policy and research center housed at the World Bank) highlights three (see Figure 1). First, the process from loan application through approval is nearly instantaneous. Second, evaluation of loan applications is automated, since digital credit products leverage historical user data (often capturing mobile phone and mobile money use) to generate credit scores. Third, loans can be processed remotely, without requiring the customer to visit a store or agent in person.

A final distinguishing feature of digital credit is that loan decisions are frequently determined

⁴While mobile money account ownership has increased quite rapidly, it is important to note that transactions are still largely cash-based, even in countries with high mobile account penetration. In Tanzania, only 53 percent of registered mobile money users left the cash in their e-wallet for more than a few days; others cash out their account balance with mobile money agents quite frequently (Mirzoyants, 2013).

⁵For example, see Dupas et al. (2016) for evidence that few people in Western Kenya used mobile money accounts to save in 2010-12.

⁶See Mbiti and Weil (2016) for a discussion of this in regards to M-Pesa.

⁷Safaricom operated two mobile loan platforms – M-Shwari in partnership with CBA, and KCB M-pesa in partnership with Kenya Commercial Bank.

⁸Safaricom reports that it currently makes two loans in the range of USD 15 to 25 every second across its two credit products . The Standard Digitalreports on borrowing across these two products.



Figure 1: Features of digital credit. Source: Chen and Mazer (2016).

based on the analysis of unconventional sources of digital data, rather than the traditional credit scores calculated by a traditional credit bureau. This is particularly relevant in developing countries, where most households do not have credit scores, due both to the underdevelopment of credit bureaus and to the fact that many people do not have a history of financial transactions which can be verified by a lender.

2.2 Digital Credit Products

2.2.1 Consumer Credit Products

The currently dominant form of digital credit is short-term, high interest rate loans made directly to consumers. Table 2 shows some information on a sampling of digital credit products. In the most common scenario, which is a bank-telco partnership, the bank originates the loan, but customer interactions – including loan disbursement and repayment – are done via the mobile money platform. Loan amounts are not very large - the average M-Shwari loan is about USD 12 (Cook and McKay 2015). Loan terms are typically no longer than a month (e.g., M-Shwari) but may be as short as a week (e.g., Airtel Malawi). Though consumers are not usually officially charged an interest rate, they are instead charged a fixed “facilitation fee.” As summarized in Table 2, these fees tend to be sizeable: ranging from 7.5% per month for M-Shwari (138% APR) to 10% per week for the Kutchova product from Airtel Malawi (over 1,000% APR). Late fees vary from provider to provider, and loans are not usually collateralized. While some companies automatically deduct mobile money balances in the case of late payment, companies are typically not able to deduct directly from airtime recharges (the mobile money and airtime systems are normally separate).

As in traditional models of lending, providers of digital credit employ dynamic incentives and punishment to reduce moral hazard and to incentivize repayment. Timely repayment of M-Shwari

loans increases the probability of getting a larger loan in the future. Customers of Branch – an app-based lender – who repay their loans on time are more likely to qualify for larger loans (increasing from USD 2.50 to USD 500), with longer repayment periods (increasing from 2 weeks up to 1 year), and at lower interest rates (with APR ranging from 180 percent to 15 percent). Interest rates on many products, like Timiza Wakala loans and Tigo Nivushe loans provided by Airtel Tanzania and Tigo Pesa respectively, are determined largely by previous borrowing behavior. Further, many existing digital loan providers discourage default by one or more of these punishments: affecting access to future loans, automatic deduction of outstanding loan amount from linked mobile savings or mobile money accounts, or blacklisting defaulting borrowers with credit bureaus.

2.2.2 Other digital credit products

While bank-telco partnerships are currently dominant,⁹ digital credit is a sector seeing rapid innovation. For instance, several financial technology (“fintech”) companies provide intermediary credit-scoring services, aggregating customer data and applying machine learning algorithms to convert the data into credit scores, which are then provided to banks and other loan originators.¹⁰ Another set of companies directly originate loans to customers, but require applicants to install an app on their smartphone that tracks and analyzes phone usage (including phone and SMS activity, handset details, GPS data, and so forth) to determine loan eligibility.¹¹

There are several digital credit products that do not directly target micro-loans to consumers. For example, Grundfos Lifelink works with Safaricom to provide pay-as-you-go solutions for clean water distribution systems to rural Kenyan communities. Similarly, Safaricom partners with M-Kopa and MTN with Mobisol and Fenix International to sell solar home solutions on a down payment. Future payments are collected via regular mobile money transactions. Enforcement of repayment is accomplished through technology which allows the firm to turn off the solar panel remotely if the account is in default. Another Safaricom credit product - Okoa Stima - allows customers to get cash advances to pay for electricity. Many telecom operators provide airtime advances using mobile loans. Examples include Safaricom’s Okoa Jahazi and Airtel’s Kutapa and Beerako in Malawi and Uganda respectively. Finally, some lenders provide digital credit to businesses, usually to business owners who use mobile payments platforms. Transactions on the payment platform is an important factor in determining creditworthiness. An example is Kopo Kopo’s credit product (Grow) for businesses that use its payment platform.¹²

⁹As of December 2015, 85 percent of global digital credit services were partnerships between a mobile operator and a financial institution (GSMA, 2015).

¹⁰Examples include Jumo and Cignifi.

¹¹Examples include Branch and Tala.

¹²Kopo Kopo’s payment platform is designed to encourage business growth, without costly monitoring and unfair punishments. Businesses repay loans by automatically allocating a pre-determined percentage of their daily business revenue towards loan repayment. Thus, firms are not punished for being unable to repay in times of poor business. Kopo Kopo incentivizes borrowers to repay early by offering lower loan fees for higher daily deduction percentages.

2.3 Competition among lenders

A competitive lending market can potentially lower the costs of scoring and disbursing loans to lenders, and help borrowers access more affordable credit. For instance, estimates from a joint CGAP-McKinsey exercise indicate that credit scoring based on nontraditional data reduces the cost of providing a USD 200 loan by 30 percent in Tanzania (Chen and Faz, 2015). However, as we have highlighted, digital credit tends to be very expensive, in part because the telecom industry is very concentrated and lenders have considerable market power. A key feature of digital credit is generating credit scores from digitized financial transactions. Since credit bureaus are non-existent or poorly functioning in many settings, this may allow for credit scoring of people excluded from the normal financial system. A major downside of this, however, is that this information is proprietary and firms have little incentive to share, so that transactions on a mobile money network are only useful for scores on that network. This may tend to increase the market power of telecom companies.

3 What is new about digital credit?

Digital credit may offer several important advantages compared to microcredit or existing bank credit.

3.1 Credit scoring

Many developing countries either do not have credit bureaus or do not have very effective ones (World Bank 2016; Luoto et al. 2007; de Janvry et al. 2010). In addition, many low-income people in developing countries do not leave “financial footprints” (such as a history of usage of financial products and services) that can be incorporated into a credit score because their financial transactions are simply not recorded, which makes credit scoring difficult. By contrast, an estimated 80% of adults in emerging economies own a mobile phone (McKinsey Global Institute, 2016), and recent evidence shows that mobile phone usage can be used to predict loan default (Björkegren and Grissen, 2015) as well as a broader range of socioeconomic characteristics of would-be borrowers (Blumenstock et al, 2015). In this environment, using mobile money to generate scores could expand credit access, especially in countries with high usage rates of mobile money accounts (see Table 1). To take one example, only 6.5% of adult Tanzanians appear in one of the country’s private credit bureaus (World Bank, Doing Business project, 2016), while 32.4% have mobile money accounts (Global Financial Inclusion Database, 2015).

The information leveraged by digital credit lenders to determine creditworthiness is varied. Most lenders from (or associated with) the telecom industry use the applicant’s history of mobile phone usage, including phone calls, text messages, airtime purchases, data use, and mobile money transactions. When the applicant has an app installed on her smartphone, this app collects all of that information as well as GPS data, information on social media use, contacts lists, and the like. For example, Lenddo uses information about contacts, frequency of interaction, interests, messaging and browser history, apps, wifi network use, and even mobile phone battery levels, among

other data points, to establish a “LenddoScore” as a measure of creditworthiness (King, 2016). FirstAccess uses demographic, geographic, financial, and social data to determine creditworthiness. VisualDNA and Entrepreneurial Finance Labs (EFL) rely on psychometric analyses to determine creditworthiness. Revolution Credit provides online financial education videos and quizzes throughout the loan process to measure creditworthiness. Other information used to create non-traditional credit scores include histories of remittance transaction (Axis Bank, and Suvidha Infoserve) and usage of payment platforms (AMP Credit, Kopo Kopo).

3.2 Reduced Transaction Costs

Bank penetration in developing countries is still fairly limited, particularly in rural areas, and thus travel costs to bank branches can be substantial. Such transactions costs can be an impediment to bank usage (see Dupas et al. 2016 for evidence from Malawi and Uganda on the effect of distance on bank usage). Banking services are also often poor, featuring long wait times or limited operating hours, and many people may not fully trust banks (Dupas et al 2016; Bachas et al 2016). Group-based microcredit banks also tend to require regular repayment of loans and regular attendance at meetings, which increase transactions costs. To the poor, transaction costs can be formidable barrier to accessing financial services (Karlan et al., 2016).

Digital credit can dramatically reduce these transactions costs, since e-cash can be transferred instantaneously and there is a much larger number of mobile money agents than bank branches (i.e. Jack and Suri 2014). Table 3 reports the reach of commercial banks and active agent outlets in five countries where digital financial services are relatively more common (Bangladesh, Kenya, Pakistan, Tanzania, and Uganda). The number of agents is often an order of magnitude higher than bank branches. While these agents face other well-documented constraints (especially in the earlier stages of mobile money adoption), for example that they lack liquidity to allow people to cash out or that networks may be down, the sheer volume of agents suggests that a well-run network can lower transaction costs significantly relative to traditional bank-based credit.

3.3 Instantaneous loan approval and disbursement

A vast literature has shown that poor people are unable to effectively deal with income shocks (see Dercon 2002 for a review). Digital credit might be very useful for shocks (just as mobile money transfers have been), since loans can be made remotely and instantaneously, with no need for human mediation. This is a particularly vivid contrast compared with the more traditional microcredit model in the spirit of the Grameen Bank, in which loans are typically geared towards productive investment and can usually be accessed only at pre-specified times. However, even for banks which allow loans for consumption, sending out loans instantly is a radical improvement.

Descriptive evidence is consistent with consumers often using loans for liquidity needs. The nationally representative FinAccess 2016 surveys in Kenya asked a question about what the main type of credit was that people accessed in times of need. People were much more likely to report digital credit (40.9%) or informal providers (40.9%) than traditional banks (6.7%) or microfinance

1.8%). In addition, credit to meet “day to day needs” is accessed most commonly from digital credit (46.2%) or informal providers (36%) than banks (5.9%) or microfinance institutions (3.6%) (Central Bank of Kenya, Kenya National Bureau of Statistics & FSD Kenya, 2016). Costa et al. (2016) discuss interviews conducted by the Omidyar Network with early adopters of digital credit in major cities of Kenya and Colombia—nearly 60 percent of mobile borrowing is driven by unforeseen expenditures and debt repayment.

3.4 Product customization

Particularly among fintech firms, there is a culture of applying recent algorithmic developments – many of which were first tested in the context of internet-based advertising – to customize and optimize lending decisions and loan terms. While in theory such technology could also be utilized by traditional bank-based lenders, the data-rich environment of digital credit is particularly well-suited to such targeted customization. For instance, the supervised learning algorithms used to predict default risk can be updated frequently, quickly adapting to changing lending conditions and aggregate risk. It is also quite common that digital credit loans will employ dynamic incentives, such that borrowers become eligible for larger loans if they reliably repay smaller loans. More sophisticated systems offer different loan repayment periods. Given the near absence of regulation in this space (more on this below), lenders have considerable scope to develop proprietary and discriminatory pricing and lending systems.

3.5 Other possible differences

Trust in financial institutions is another factor impeding financial access (Demirguc-Kunt et al. 2014; Dupas et al. 2016).¹³ It is conceivable that digital credit would be relatively more trusted, since loans are provided by established telecom providers. These firms tend to be familiar and trusted, and their products (mobile phone services, mobile money) are used more regularly than those of microcredit institutions and banks. However, there are also anecdotes of people not trusting agents. Some agents have trouble holding enough liquidity to meet withdrawal requests, particularly in rural areas where many transactions are withdrawals of remittances sent from urban areas.¹⁴ In some systems, agents have an incentive to strategically control their liquidity or to lie about liquidity to maximize revenue (Jumah 2015).¹⁵ It thus remains to be seen whether digital credit will offer trust advantages over financial institutions.

¹³Some reasons cited in the 2016 FinAccess Household Surveys for stopping usage of bank accounts in Kenya include banks not meeting needs of customers (19.7%), hidden charges (14.1%), money lost or taken by bank (12.7%), and people being dissatisfied with bank service (12%) (Central Bank of Kenya, Kenya National Bureau of Statistics & FSD Kenya, 2016).

¹⁴One policy to increase agent liquidity is for mobile money providers to provide credit to the agents. One example of a provider doing this is Airtel Tanzania, which launched Timiza Wakala loans in 2015. These digital loans, which range from USD 23 to USD 229, are provided to help qualifying Airtel mobile money agents meet their business needs.

¹⁵Anecdotal reports also suggest that customers often leave cash and PIN numbers with mobile money agents during network downtimes so that agents can carry out transactions on their behalf, and that this practice exposes mobile money users to fraud (McKee et al. 2015).

4 Open questions

Over the course of just a few years, digital credit has proliferated rapidly in several developing countries, and demand for these products is accelerating across the globe. To our knowledge, however, not a single quantitative impact evaluation has rigorously measured the social and economic impacts of digital credit.¹⁶ More broadly, there is a dearth of empirical evidence that can help development policymakers and regulators understand the implications of this financial transformation. Here, we briefly mention several questions that we believe deserve the attention of the research community.

4.1 What is the impact of digital credit?

Digital credit is a very recent innovation, and represents a truly new way of accessing loans and thus impacts may differ from more traditional microcredit. While there is a lack of current research on the topic, there exists a time-limited window for conducting research in this space. Since products are just now being rolled out in new countries, there exist immediate opportunities to study these effects through randomized experiments (such as randomized offers or encouragement designs), natural experiments, as well as other non-experimental approaches (such as a regression discontinuity around an eligibility threshold).

In such studies, it is important to consider the possibility that digital credit may have negative as well as positive effects. One likely benefit of digital credit would be to help borrowers with short-term liquidity needs,¹⁷ but a variety of plausible theories of change might be worthy of research.¹⁸ At the same time, as we discuss in greater detail below, unsophisticated borrowers may borrow too much, may get shut out of the system through accidental default, or suffer in other unintended ways.

This is a context in which heterogeneity is certainly important. While some people will likely benefit from having easy access to cash in times of high liquidity needs, others may take out loans that they do not need. For example, time-inconsistent or less financially sophisticated borrowers may be tempted to take out high-interest loans because they are so easy to access (i.e. Meier and Sprenger, 2010; Heidhues and Koszegi, 2010). Research should carefully consider heterogeneity in positive as well as negative impacts of digital credit.

It is also important to understand who are the winners and who are the losers in this ecosystem. Initial evidence indicates that early adopters of digital credit products are likely to be young, male, urban, educated, stably employed, bank account holders, and report being able to cover their basic expenses and save (Cook and McKay 2015; Costa et al. 2015). It is not surprising that the tech-

¹⁶The one ongoing evaluation we are aware of is being conducted by Prashant Bharadwaj, William Jack, and Tavneet Suri with M-Shwari in Kenya.

¹⁷Thus researchers would likely need to focus on the responsiveness of households to shocks and other adverse events, and examine whether credit may help mitigate these shocks. Researchers may be able to anticipate likely effects simply from looking at loan uses.

¹⁸For instance, if consumers tend to use loans for other purposes, like business investment, loans will be unlikely to be effective unless available investment opportunities truly exceed 100% per year or more.

savvy with deeper digital footprints are the first to access digital credit. The demographics of users of digital credit is very likely to change over time: initial adopters of mobile money were more likely to be urban and wealthy, but the number of rural, and poor users of mobile money increased over time (Jack and Suri 2014).

4.2 Consumer Protection

Digital credit brings financial services to many who have never before participated in a formal financial system. This can be a double-edged sword. On the one hand, this furthers efforts for financial inclusion. On the other, the target client base have little to no experience working with a financial institution, let alone through complicated user interfaces. For example, in Rwanda, only about half of borrowers report knowing their loan terms and the interest they pay on loans (InterMedia 2015). Focus groups run by CGAP and evidence from diary respondents indicate that customers have little awareness of the products, fees, and terms of the loan, and several respondents report taking their first loan without an intentional purpose for it (see Mazer and Fiorillo, 2015; McKee et al 2015). More broadly, less sophisticated borrowers may be especially susceptible to over-borrowing (Meier and Sprenger, 2010; Heidhues and Kőszegi, 2010), especially when a loan is accessible by dialing in a request on their mobile phones. And, conditional on borrowing, people with time-inconsistent preferences may find it more difficult to repay loans.

The procedure of obtaining informed consent with digital credit may be ineffective in really informing customers of their rights and the data that is being used. Most digital credit products direct customers to a website to understand the terms and conditions of the product – it is unlikely that many have the resources (like internet connectivity) to access this information. Simply reading long loan descriptions is challenging on a feature phone. CGAP provides insights regarding how customers perceive the informed consent procedure from interviews and focus group discussion with 64 individuals in Tanzania. While their participants were willing to share data to access credit, they wanted more information about how their data is accessed and how it would be used than is currently provided by digital credit providers (Mazer et al., 2014).

Digital credit products also raises a host of privacy issues. The data most commonly used on digital credit platforms are data that most people would consider private, and it is not clear that borrowers fully understand how such data is being used in determining loan eligibility. In more developed financial ecosystems, regulatory agencies (such as the Federal Trade Commission in the U.S.) oversee these institutions and determine how such data can be used, but such institutions are generally weak or nonexistent in the markets where digital credit is thriving.

Non-traditional scoring retains some trappings of traditional credit scoring models. Research shows that such models can acquire implicit biases based on gender and race (cf. Caliskan et al, 2017), and there is reason to think that such biases might be more severe in contexts where non-traditional data is used to predict default. In some cases, algorithms explicitly utilize information on borrower’s social networks. For instance, Lenddo asks its borrowers to select a “Trusted Network” of at least three people. When a borrower defaults, this trusted network’s Lenddo scores

suffer and they become less likely to qualify for a loan with Lenddo (Hardeman, 2012). It is also important to keep in mind that many who are financially excluded are likely to have shallow digital footprints. Scoring based on this data may need to be supplemented with other measures of creditworthiness, particularly when the consequences of default are so severe. While recent advances in machine learning provide options for “fair” predictive algorithms, a naive implementation could systematically exclude precisely those populations for whom digital credit might have the greatest positive impacts.

Separately, many lenders report concerns of fraud, from borrowers who register multiple accounts, to middlemen who resell SIM cards that have been approved for loans, to clients who deliberately manipulate their behavior to become eligible for larger loans.¹⁹ If not contained, such behavior could threaten the broader ecosystem. Again, models and algorithms exist to detect and account for strategic and adversarial borrowers, but determining how to effectively integrate such insights into digital credit systems will require careful thought.

4.3 Product innovation and other lending models

Digital credit has been dominated by small, short-term, high interest rate loans. But can credit be delivered through alternative means, for example through supply chains? Should data analytics be complemented with information contained in value chains to increase effectiveness of credit? For example, Maitra et al. (2014) show that borrowers selected by traders increased production of cash crop and farm income more than farmers who were given microcredit. Or, what are the effects of credit being distributed through networks that restrict their usage? Tienda Pago pays distributors directly for inventory that is then delivered to the shop-owners; these shop owners repay Tienda Pago from sales revenue, via electronic mobile payment platform.

And while consumer loans are currently dominant and are the focus of this review, digital credit can be used with other lending models. For example, firms like M-Kopa and Fenix International sell solar panels to households on a down payment, and collect repayment via regular mobile money transactions. Enforcement of repayment is accomplished through technology which allows the firm to turn off the solar panel remotely if the account is in default. The reduction in transaction costs from mobile money makes this type of model viable.

5 Conclusion

In the past several years, digital credit has rapidly proliferated in the developing world, particularly in Sub-Saharan Africa, yet there is virtually no quantitative research to examine its effects. Digital credit offers several substantial improvements relative to traditional credit, notably large reductions in transactions costs, near-instantaneous loan approval and disbursement, and an expansion in the consumer base resulting from using nontraditional data to generate credit scores. Yet the current

¹⁹Mudiri (2013) discusses fraud in digital financial services. McKee et al. (2015) provide a summary of key customer risk areas in digital credit.

products that are available are largely high interest rate, short-term loans that look very similar to payday loans in the developed world. In this environment, easy access to high interest rate loans is likely to have heterogeneous effects, potentially providing liquidity in times of need for some people while encouraging others to take out loans that they do not need (for example, less sophisticated or present-biased borrowers).

We have reviewed several open areas for research, starting with the most basic and important – documenting the positive and negative impacts of digital credit on consumers, and examining how effects may vary with borrower characteristics. Another important research area is in consumer protection, since existing protections tend to be weak in many markets in which digital credit is dominant, and anecdotal evidence suggests some borrowers have limited knowledge about loan terms. More work can be done to understand and refine the algorithms used by lenders to determine creditworthiness. A final question we have highlighted is whether digital credit can be integrated into lending models other than consumer credit, for example into supply chains.

While there is virtually no quantitative evidence in the area, the policy implications of scholarship in this area are large, since so many people have either recently gotten access to digital loans or will be getting access in the coming years. And since digital credit is not yet scaled up, there is an opportunity to partner with lenders or telco companies during the expansion phase. For both reasons, we argue that the current moment offers a unique opportunity to do research in digital credit.

References

- [1] Aglionby, John (2016). Tanzania’s fintech and mobile money transform business practice. *Financial Times*, July 12, 2016.
- [2] Banerjee, Abhijit and Esther Duflo (2014). “Do firms want to borrow more? Testing credit constraints using a directed lending program.” *Review of Economic Studies* 81 (2): 572-607.
- [3] Banerjee, Abhijit, Dean Karlan and Jonathan Zinman. (2015). “Six randomized evaluations of microcredit: Introduction and further steps.” *American Economic Journal: Applied Economics* 7 (1):1–21.
- [4] Bachas, Pierre, Paul Gertler, Sean Higgins, and Enrique Seira. (2017). “Banking on Trust: How Debit Cards Enable the Poor to Save More.” National Bureau of Economic Research Working Paper w23252.
- [5] Bertrand, Marianne and Adair Morse (2011). “Information disclosure, cognitive biases, and payday borrowing.” *Journal of Finance* 66 (6): 1865-1893.
- [6] Bhutta, Neil, Paige Marta Skiba and Jeremy Tobacman (2015). “Payday Loan Choices and Consequences.” *Journal of Money, Credit and Banking* 47 (2-3): 223-260.
- [7] Bjorkegren, Daniel and Daniel Grissen (2015). “Behavior revealed in mobile phone usage predicts loan repayment.” Unpublished.
- [8] Blumenstock, Joshua, Gabriel Cadamuro and Robert On(2015). “Predicting poverty and wealth from mobile phone metadata.” *Science* 350 (6264): 1073-1076.
- [9] Caliskan, Aylin, Joanna J. Bryson and Arvind Narayanan (2017). “Semantics derived automatically from language corpora contain human-like biases.” *Science* 356 (6334): 183-186.
- [10] Central Bank of Kenya, Kenya National Bureau of Statistics & FSD Kenya (2016). “The 2016 FinAccess Household Survey on financial inclusion.” Nairobi, Kenya: FSD Kenya.
- [11] Chen, Gregory and Xavier Faz (2015). “The Potential of Digital Data: How Far Can It Advance Financial Inclusion?” Focus Note 100. Washington, D.C.: CGAP, January
- [12] Chen, Greg and Rafe Mazer, R. (2016). “Instant, Automated, Remote: The Key Attributes of Digital Credit.” CGAP Blog, February 8, 2016. [http:// www.cgap.org/blog/instant-automated-remote-key- attributes-digital-credit](http://www.cgap.org/blog/instant-automated-remote-key-attributes-digital-credit)
- [13] Cook, Tamara and Claudia McKay. (2015). “How M-Shwari works: The story so far.” Consultative Group to Assist the Poor (CGAP).
- [14] Costa, Arjuna, Anamitra Deb and Michael Kubzansky. (2015). “Big Data, Small Credit: The Digital Revolution and Its Impact on Emerging Market Consumers.” *innovations* 10 (3-4): 49-80.
- [15] Dercon, Stefan. (2002). “Income risk, coping strategies, and safety nets.” *The World Bank Research Observer*, 17(2), 141-166.

- [16] De Janvry, Alain, Craig McIntosh and Elisabeth Sadoulet. (2010). “The supply-and demand-side impacts of credit market information.” *Journal of Development Economics* 93 (2): 173-188.
- [17] de Mel, Suresh, David McKenzie, and Christopher Woodruff. (2008). “Returns to capital in microenterprises: evidence from a field experiment.” *Quarterly Journal of Economics* 123 (4): 1329–1372.
- [18] Demirguc-Kunt, Asli, Leora Klapper, Dorothe Singer and Peter Van Oudheusden (2015). “The Global Findex Database 2014: Measuring Financial Inclusion around the World.” World Bank Policy Research Working Paper 7255.
- [19] Devoto, Florencia, Esther Duflo, Pascaline Dupas, William Pariente, and Vincent Pons. 2012. “Happiness on Tap: Piped Water Adoption in Urban Morocco.” *American Economic Journal: Economic Policy* 4 (4): 68–99
- [20] Dupas, Pascaline, Sarah Green, Anthony Keats and Jonathan Robinson. (2016) “Challenges in Banking the Rural Poor: Evidence from Kenya’s Western Province.” NBER Volume *African Successes: Modernization and Development* Volume 3. Sebastian Edwards, Simon Johnson, and David N. Weil, editors, University of Chicago Press.
- [21] Dupas, Pascaline, Dean Karlan, Jonathan Robinson, and Diego Ubfal (2017). “Banking the Unbanked? Evidence from three countries.” Forthcoming, *American Economic Journal: Applied Economics*.
- [22] Dupas, Pascaline and Jonathan Robinson. (2013). “Why don’t the poor save more? Evidence from health savings experiments.” *American Economic Review* 103 (4): 1138-1171.
- [23] Fafchamps, M., McKenzie, D., Quinn, S., & Woodruff, C. (2014). Microenterprise growth and the flypaper effect: Evidence from a randomized experiment in Ghana. *Journal of development Economics*, 106, 211-226.
- [24] Gertler, Paul, and Jonathan Gruber. 2002. ”Insuring Consumption Against Illness .” *American Economic Review*, 92(1): 51-70.
- [25] GSMA (2015). “2015 Mobile Insurance, Savings & Credit Report.” <https://www.gsma.com/mobilefordevelopment/wp-content/uploads/2016/08/Mobile-Insurance-Savings-Credit-Report-2015.pdf>.
- [26] GSMA (2016a). “State of the Industry Report on Mobile Money Decade Edition: 2006 - 2016.” http://www.gsma.com/mobilefordevelopment/wp-content/uploads/2017/03/GSMA_State-of-the-Industry-Report-on-Mobile-Money_2016.pdf.
- [27] GSMA (2016b). *The Mobile Economy 2016*. <http://www.gsma.com/mobileeconomy/>
- [28] Hardeman, Bethy. (2012). “Lenddo’s Social Credit Score: How Who You Know Might Affect Your Next Loan.” *Huffington Post Blog*, August 14, 2012.

- [29] Heidhues, Paul, and Botond Koszegi. (2010). "Exploiting Naivete about Self-Control in the Credit Market." *American Economic Review* 100 (5): 2279-2303.
- [30] Intermedia. (2015). "Financial Inclusion Insights (FII) Data. Bangladesh, Pakistan, Kenya, Tanzania, Uganda, Rwanda, Ghana." Washington D.C.: InterMedia.
- [31] Jack, William and Tavneet Suri (2014). "Risk Sharing and Transaction Costs: Evidence from Kenya's Mobile Money Revolution." *American Economic Review* 104 (1): 183-223.
- [32] Jack, William and Tavneet Suri (2017). "The Long Run Poverty and Gender Impacts of Mobile Money." *Science* 354 (6317): 1288-1292.
- [33] Jumah, Jaqueline. (2015). "The 'I Don't Have Enough Float' Quandary!" Microsave Blog, <http://blog.microsave.net/the-i-dont-have-enough-float-quandary/>.
- [34] Karlan, Dean and Jonathan Zinman (2010). "Expanding Credit Access: Using Randomized Supply Decisions to Estimate the Impacts." *Review of Financial Studies* 23 (1): 433-464.
- [35] Karlan, Dean, Jake Kendall, Rebecca Mann, Rohini Pande, Tavneet Suri and Jonathan Zinman. (2016). "Research and Impact of Digital Financial Services." *NBER Working Paper 22633*.
- [36] King, Hope. (2016). This startup uses battery life to determine credit scores. *CNN*, 24 August 2016.
- [37] Lauer, Kate and Timothy Lyman. (2005). "Digital Financial Inclusion." CGAP Brief, <http://www.cgap.org/sites/default/files/Brief-Digital-Financial-Inclusion-Feb-2015.pdf>.
- [38] Luoto, Jill, Craig McIntosh and Bruce Wydick. (2007). "Credit information systems in less developed countries: A test with microfinance in Guatemala." *Economic Development and Cultural Change*, 55(2), 313-334.
- [39] Maitra, P., Mitra, S., Mookherjee, D., Motta, A., & Visaria, S. (2014). "Financing Smallholder Agriculture: An Experiment with Agent-Intermediated Microloans in India." *National Bureau of Economic Research* (No. w20709).
- [40] Mazer, Rafe, Jessica Carta and Michelle Kaffenberger M. (2014). "Informed Consent How Do We Make It Work for Mobile Credit Scoring?" CGAP Blog, February 8, 2016, <http://www.cgap.org/publications/informed-consent-how-do-we-make-it-work-mobile-credit-scoring>.
- [41] Mazer, Rafe and Alexandra Fiorillo (2015). "Digital Credit: Consumer Protection for M-Shwari and M-Pawa Users." CGAP Blog, April 21, 2015, <http://www.cgap.org/blog/digital-credit-consumer-protection-m-shwari-and-m-pawa-users>.
- [42] Mbiti, Isaac and David Weil (2016). "Mobile Banking: The Impact of M-Pesa in Kenya." Published in *African Successes, Volume III: Modernization and Development*, editors Sebastian Edwards, Simon Johnson, and David N. Weil, p. 247 - 293. University of Chicago Press and NBER.

- [43] McKee, Kate, Michelle Kaffenberger and Jamie Zimmerman (2015). “Doing Digital Finance Right: The Case for Stronger Mitigation of Customer Risks.” CGAP Focus Note No. 103.
- [44] McKinsey Global Institute. (2016). “Digital Finance for All: Powering Inclusive Growth in Emerging Economies.” <http://www.mckinsey.com/global-themes/employment-and-growth/how-digital-finance-could-boost-growth-in-emerging-economies>.
- [45] Meier, Stephen and Chales Sprenger. (2010). “Present-biased preferences and credit card borrowing.” *American Economic Journal: Applied Economics*, 2 (1): 193-210.
- [46] Melzer, Brian. (2011). “The real costs of credit access: Evidence from the payday lending market.” *Quarterly Journal of Economics* 126 (1): 517-555.
- [47] Mirzoyants, A. (2013). “Mobile Money in Tanzania: Use, Barriers and Opportunities.” Intermedia Financial Inclusion Tracker Surveys Project, http://www.intermedia.org/wp-content/uploads/FITS_Tanzania_FullReport_final.pdf.
- [48] Morse, Adair (2011). “Payday lenders: Heroes or villains?” *Journal of Financial Economics* 102 (1): 28-44.
- [49] Mudiri, Joseck Luminzu. (2013). ”Fraud in mobile financial services.” Rapport technique, MicroSave, http://www.microsave.net/files/pdf/RP151_Fraud_in_Mobile_Financial_Services_JMudiri.pdf.
- [50] Skiba, Paige Marta and Jeremy Tobacman (2009). “Do Payday Loans Cause Bankruptcy?” Unpublished.
- [51] Tarozzi, Alessandro, Aprajit Mahajan, Brian Blackburn, Dan Kopf, Lakshmi Krishnan, and Joanne Yoong. (2014). “Micro-loans, insecticide-treated bednets, and malaria: evidence from a randomized controlled trial in Orissa, India.” *American Economic Review* 104 (7): 1909-1941.
- [52] World Bank. (2015). “*Global Financial Inclusion Database*.” <http://www.worldbank.org/en/programs/globalindex>.
- [53] World Bank. (2016). *World Development Report 2016: Digital Dividends*. Washington, DC: World Bank.
- [54] World Bank. (2017). *Doing Business 2017: Equal Opportunity for All*. Washington, DC: World Bank.
- [55] Udry, Christopher and Santosh Anagol. (2006). “The return to capital in Ghana.” *American Economic Review*, 96(2): 388-393.

Table 1. Global account ownership

	(1)	(2)
	Has an account at a financial institution ¹ (%)	Has a mobile money account ² (%)
Argentina	50.2	0.4
Bangladesh	29.1	2.7
Botswana	49.2	20.8
Burkina Faso	13.4	3.1
Cambodia	12.6	13.3
Chile	63.2	3.8
China	78.9	--
Congo, Dem Rep.	10.9	9.2
Cote d'Ivoire	15.1	24.3
Dominican Republic	54.0	2.3
Ecuador	46.2	--
Egypt	13.7	1.1
Ethiopia	21.8	0.0
El Salvador	34.6	4.6
Gabon	30.2	6.6
Ghana	34.6	13.0
India	52.8	2.4
Indonesia	35.9	0.4
Kenya	55.2	58.4
Madagascar	5.7	4.4
Malawi	16.1	3.8
Mali	13.3	11.6
Mexico	38.7	3.4
Namibia	58.1	10.4
Nigeria	44.2	2.3
Pakistan	8.7	5.8
Philippines	28.1	4.2
Rwanda	38.1	18.1
South Africa	68.8	14.4
Tanzania	19.0	32.4
Uganda	27.8	35.1
Vietnam	30.9	0.5
Zambia	31.3	12.1
Zimbabwe	17.2	21.6

Source: Global Financial Inclusion (Global Findex) Database 2014, World Bank Group

¹Percentage of respondents who report having an account (by themselves or together with someone else) at a bank or another type of financial institution; having a debit card in their own name; receiving wages, government transfers, or payments for agricultural products into an account at a financial institution in the past 12 months; paying utility bills or school fees from an account at a financial institution in the past 12 months; or receiving wages or government transfers into a card in the past 12 months (% age 15+).

²Percentage of respondents who report personally using a mobile phone to pay bills or to send or receive money through a GSM Association (GSMA) Mobile Money for the Unbanked (MMU) service in the past 12 months; or receiving wages, government transfers, or payments for agricultural products through a mobile phone in the past 12 months (% age 15+).

Table 2. Sample of Digital Credit Products

(1) Product	(2) Country	(3) Start Year	(4) Provider	(5) Qualifying requirements	(6) Fees	(7) Maturity	(8) Customer base ¹
M-Shwari	Kenya	2012	Safaricom & Commercial Bank of Africa	Active user of M-Shwari savings, and other Safaricom products	Facilitation fee: 7.5%	1 month	3.9m active 30 day users (Mar, 2016)
KCB M-Pesa	Kenya	2015	Safaricom & Kenya Commerical Bank	Active M-pesa account	Facilitation fee of 2.5% + monthly interest of 11.6%	1 month	0.73m active 30 day users (Mar, 2016)
Branch	Kenya	2015	Branch	Registered M-pesa user, active social media (e.g. Facebook) user	1%-14% pm	2 weeks- 1 year	100,000 borrowers (Sep, 2016)
Equitel Eazzy Loan	Kenya	2015	Equity Bank Group	Registered Equitel user; active account with Equity Bank	14%	1 month	3.5 million loans worth Sh30 billion issued in year ending 9/16
Tala	Multiple	2014	Tala	Registered Tala users	11%-15%	1 month	100,000 borrowers in July, 2016
Grow	Kenya	2016	Kopo Kopo	Merchant credit for Kopo Kopo's payments platform users	Fixed fee: 1%	Until repaid	-
Timiza Loans	Tanzania	2014	Airtel Tanzania & Jumo	Active Airtel money user	Varying	7-28 days	-
Timiza Wakala Loans	Tanzania	2015	Airtel Tanzania & Jumo	Airtel mobile money agents	Varying	7-28 days	-
M-Pawa	Tanzania	2014	Vodacom Tanzania & Commercial Bank of Africa	Active m-Pesa user	Facilitation fee: 9%	1 month	4.9 million borrowers during first two years ²
Tigo Nuvushe		2016	Tigo Pesa, Jumo	Active Tigo pesa users	Facilitation fee based on length of tenure	1-3 weeks	-
MoKash	Uganda	2016	MTN Uganda & Commercial Bank of Africa	MTN mobile money subscriber , save on MoKash and actively use other MTN services	Facilitation fee: 9%	1 month	1 million registered users within 3 months of launch. ³
Airtel Money Bosea	Ghana	2016	Airtel Ghana, Fidelity Bank Ghana, Tiaxa	Active Airtel users	10%-20% ⁴	1 month	-
Airtel Money Kutchova	Malawi	2016	Airtel, FDH Bank	Airtel money subscriber	10%	7 days	-

¹Unless otherwise noted, all information is from official lender sources.

²Aglionby, 2016.

³Reported in PC Tech Magazine <http://pctechmag.com/2016/10/mtn-mokash-reach-one-million-subscribers-milestone-after-3-months/>

⁴Reported in Ghana News Agency <http://www.ghananewsagency.org/economics/airtel-launches-airtel-money-bosea--103765>

Table 3: Bank & Agent Penetration

	(1)	(2)
	Commercial bank branches (per 100,000 adults)	Active agents (per 100,000 adults)
Bangladesh	8.4	111.0
Kenya	5.9	272.9
Pakistan	10.0	52.4
Tanzaia	2.5	236.0
Uganda	3.0	175.4

Notes: Indicator for Commercial bank branches (per 100,000 adults) is from the World Bank World Development Indicators Database. All measures are from 2015.

Active agents (per 100,000 adults) is calculated using Helix Institute's count of active agent outlets, and adult populations reported in Bersudskaya and McCaffrey (2017).

Data for Kenya and Pakistan is

from 2014, and for Bangladesh, Tanzania and Uganda, it is from 2015.