Liquidity or Convenience? Heterogeneous Impacts of Mobile Airtime Loans on Communication Expenditure

Oscar Barriga-Cabanillas[1] and Travis J. Lybbert[1]

[1] *University of California, Davis*

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Abstract

Credit market imperfections can decrease welfare by increasing vulnerability to shocks and destabilizing consumption. Meta data from individual cellphone users have enabled a proliferation of mobile financial services in markets where information asymmetries and high provision costs tend to deter formal financial institutions. As the first such financial product typically offered to new users, airtime loans provide prepaid customers small airtime advances for a fee as an alternative to recharges purchased from network agents. Relying on rich administrative data from a mobile network operator in Haiti, we study the impact of airtime loans on consumer cellphone expenditure and network usage. We find that access to loans increases total communication expenditure by 16% due to a crowding-in of additional network usage. This expenditure response to airtime loans is distinctly heterogeneous. Poorer customers in the lowest tercile of initial expenditure more than double their mobile communication spending when airtime loans become available, while access to loans leaves expenditure of the highest tercile unchanged. These differences in the expenditure impacts of airtime loans exist despite relatively uniform patterns of loan usages between the poor and non-poor. We find suggestive evidence that these differences are driven by distinct motivations for requesting airtime loans: Poorer customers appear to use loans to relax short-term liquidity constraints at critical communication times whereas non-poor customers primarily use these loans for convenience, as it gives them more discretion in when to visit airtime vendors.

JEL Classification:

Keywords: Liquidity constraints, credit, mobile phones, mobile financial services, Haiti.

1 Introduction

As cell phones have spread around the world and entered the lives of rich and poor alike, they have ushered in unprecedented financial inclusion opportunities. Mobile Financial Services (MFS) have enabled a flurry of innovation, with products that bring new ways of paying, saving, borrowing, and insuring to people and regions previously under-served by traditional financial institutions. These impressive and innovative gains have in many ways redefined economic development opportunities and even macroeconomic policy possibilities (Suri, 2017; Aron *et al.*, 2017).

The proliferation of MFS offerings we observe today in many middle and low-income countries first hinged on the widespread availability of inexpensive hardware — especially feature phones — and simple prepaid plans that allowed customers to add airtime as needed in increments of nickles and dimes. Although these breakthroughs made cellular service accessible to almost everyone, including the poor, with this access came new financial dilemmas as these costs stretched the already limited resources of poor households. As cellphones became the newest necessity, managing this new asset and the expenses associated with this vital connection to one's network became an essential part of daily budgeting. For example, one fifth of Kenyan users reports to forgo other expenditures such as food, bus fares, or utility bills in order to keep their cellphones active, and studies across different countries show poor households spend between 10 and 25% of their disposable income on mobile phone usage (Agüero *et al.*, 2011; The World Bank, 2012).[1] Nickles and dimes spent on prepaid cell service can add up fast for those living on a dollar or two a day, particularly since demand for this service is often as frequent as demand for food. Against this backdrop, managing one's prepaid balance against expected communication needs and the opportunity cost of short-term (often intra-day) liquidity becomes a non-trivial, pressing and ever-present financial imperative.

As cheap phones and prepaid plans enabled mobile network operators to reach customers that had rarely been reached by the formal sector before (much less, formal financial services), the stage was set for MFS to create entirely new financial inclusion opportunities by sidestepping the informational asymmetries and institutional limitations that continue to stymie the development of financial markets in the developing world. These traditional challenges are especially salient

[1]The survey was conducted on a representative sample of cellphone customers, see The World Bank (2012)

for those who lack formal financial histories, want small loans, and are often located in areas that are difficult to serve. Cellphone technology has two key features that make it ideal to alleviate these challenges. First, cellphone usage creates a personalized data-trail from which insights about credit worthiness can be extracted. For the unbanked poor with few collateralizable assets, such alternative credit score sources can provide a key point of departure for financial inclusion. Second, it allows for remote, and automated, processing of the transactions lowering administrative costs (Björkegren and Grissen, 2018; Bharadwaj *et al.*, 2019).[2] The potential of financial inclusion gains from these innovations became clear in the past decade as individuals with access to MFS were able to better manage and share risk, smooth consumption, and take advantage of productive opportunities (Bharadwaj *et al.*, 2019; Suri and Jack, 2016). The potential for future gains is similarly massive as familiarity grows among the billion individuals who currently have a cellphone but not a bank account (GSMA, 2014).

In this paper, we study the first rung in the financial inclusion ladder provided by MFS and evaluate its impact on communication expenditure. This MFS product provides customers airtime advances in the form of very small and very short-term loans. Each loan is, on average, less than USD$0.50. In a country where 46% of adults lack access to any formal financial service and two of every three loans come from informal lenders, friends, and family (FinScope, 2018), airtime loans represent for many poor customers the first formal financial transaction of their lives. Airtime loans are popular, with 40% of eligible customers using them every month. On average, eligible customers finance 30% of his cellphone expenditure with airtime loans, each loan incurring a 10% fee. As elsewhere, the popularity of these loans is easy to appreciate given that the flexibility of prepaid phone service comes at the cost of frequent recharges and the risk of running out of airtime at a critical moment (Jack and Smith, 2020).[3] The cost of missed calls, unsent SMS messages, and frequent visits to airtime vendors are obviously difficult to quantify, but clearly these costs

[2]The cellphone provider does not need to be directly involved in the provision of the services with many services working over multiple platforms. However, given their competitive edge, cellphone companies are the biggest players in the market.

[3]Cellphone technology is ideal for this billing scheme as there is permanent communication between the device and the service provider, and the cost of each transaction can be made explicit to the consumer. Aker and Mbiti (2010) identifies this flexibility as a key factor contributing to the rapid adoption of cellphones by less wealthy consumers. From the provider's perspective, prepayment has the advantage that it avoids costly enforcing of contracts.

fall disproportionately on liquidity-constrained customers who must weigh them against locking up their limited liquidity in the form of airtime balance. For such customers, airtime loans soften this daily dilemma and potentially alter how and how often they use the mobile network.

We use a unique dataset from the largest cellphone provider in Haiti that contains the full set of transactions in the network in 2019. We exploit the eligibility rule, which makes that customers can request their first loan five weeks after initial activation, to implement an event study to identify the impact of airtime loans on subsequent communication patterns and expenditure. We find that access to loans increases total expenditure by 16%, which represents a crowding-in of new communication expenditure well beyond the fees associated with the loan. This result is in line with finding in the credit card market where increases in credit limits generate an immediate and significant rise in consumption (Gross and Souleles, 2002).[4]

There are three mechanisms through which airtime loans could conceivably increase communication expenditure. The first mechanism includes binding liquidity constraint that forces customers to reduce their cellphone activity when they lack funds to pay for calls, making cellphone consumption sensitive to cash flows. The second mechanism involves a reduction on the salience of the costs of calls that takes place as customers can avoid visiting vendors and paying with cash. Finally, it can be the case that high transaction costs that deter consumers from recharging even when they have funds available. These mechanisms are not mutually exclusive, with different individuals being affected by each channel in a different degree. To shed light on the mechanisms, we explore for heterogeneous impacts across the income distribution. Despite relative uniform patterns of loan usages between the poor and non-poor we find distinctly heterogeneous results. Poorer customers in the lowest tercile of initial expenditure more than double their mobile communication spending when airtime loans become available. Meanwhile, access to loans leaves expenditure of the highest tercile unchanged. Why would access to airtime loans lead to an increase in the expenditure of the poor while still being attractive to better-off customers? We find suggestive evidence that these differences are driven by distinct motivations for requesting airtime loans. Consistent with binding liquidity constraints, poorer customers who often survive day-to-day on razor-thin cash balances

[4]The author find that every \$100 increase in the credit card limit increases spending between \$10 to \$14 dollars.

appear to use loans to relax liquidity constraints at times critical communication times. Considering that loans are paid relatively quickly and the high repayment rate, these results indicate the consumption levels of this group are highly sensitive to the timing of their income. This is a typical results in the presence of credit markets imperfections where the tools available to individuals in terms of cash management, savings, and borrowing are not enough to isolate consumption for (daily) cash cycles (Gelman *et al.*, 2014).

Non-poor customers, on the other hand, seem to use airtime loans primarily for their convenience. By borrowing airtime, subscribers avoid looking for airtime vendors and can strategically shift their recharges towards times with lower transaction costs. In our setting, the loan facilitation fee of 10% provides an upper bound for the perceived transaction costs of recharging at inconvenient times. This willingness to pay for convenience has been observed in other financial products where new technologies have been introduced. For example, Buchak *et al.* (2018) find that online lenders are able to charge a premium for the possibility to apply for a loan in a computer using a more friendly interface. This premium exists even when they offer a similar product as brick-and-mortar banks, and it is higher than what regulatory or financial costs could explain.

We contribute to the empirical literature on the effects of credit access in several ways. First, we investigate the most popular digital credit product an show that eligibility increases total cellphone expenditure, a result that we explain by credit access lifting pressing liquidity constrains. This result is important as we consider that more digital credit products will be launched in the future. Comparing our results with other studies is difficult as the study of airtime loans has been overlooked in favor of products that provide larger uncollaterallized loans that can be converted into cash. However, adoption of these products has been slow due to high levels of risk and deployment costs. Bharadwaj *et al.* (2019) provides the only evidence available on the effects of extending credit access through digital financial services.[5] The authors confirm that digital credit can provided access to loans to consumers excluded by formal financial services. The product they study is not completely comparable as loans can be converted into cash and are, on average, ten times larger that the average airtime loan.[6] Interestingly, an important percentage is still used to cover airtime. Similar

[5]There is an ongoing study of a digital credit product in Tanzania, but results are not yet available.

[6]4.8 dollars against USD$0.50

to our finding, they observe a large demand for additional liquidity that digital credit seems to be ideally designed to supply. Their results are encouraging as they show digital credit increases the resilience of households to shocks, with credit access allowing households to finance unexpected expenditures that otherwise the household lacks the liquidity to pay.[7] Their identification strategy allows them to identify effects only for people with high levels of poverty and not significant access to other credit sources. In this sense, we add to the literature by showing how better-off consumers respond to an increase on their total borrowing capacity, highlighting the role of easy access to loans on fostering demand for credit.

Second, we contribute to the understanding of how demand for digital loans responds to both liquidity needs and, for some, convenience. This convenience effect dominates in customers with relatively high income and raises concerns about how digital credit can potentially create overindebetdness problems. Evidence suggests that the expedience of fund delivery has a detrimental effect on the repayment probability (Bulando *et al.*, 2020), with consumer credit having positive effects only when borrowing responds to unexpected shocks. Otherwise, borrowers are likely to fall into overindebetdness, and lose future access to formal credit options (Carrell and Zinman, 2014; Skiba and Tobacman, 2019; Ausubel, 1991; Bond *et al.*, 2009; Morse, 2011; Zinman, 2010; Karlan and Zinman, 2010).

As our last contribution, we exploit a high-frequency administrative dataset to identify the impacts of airtime loans. Different studies have shown that there are distinct signals in the cellphone transaction data that can be used to predict the poverty and wealth of individual subscribers (Blumenstock *et al.*, 2015; Frias-Martinez *et al.*, 2013). However, little is known about how people with less economic means manage their accounts to maximize their utility from communication given their financial constraints. We exploit the high-resolution in the date, to identify effects that traditional surveys, even those that collect detail expenditure records have trouble identifying (Gelman *et al.*, 2014).

The paper continues as follows. Section 2 explains how airtime loans fit into the ecosystem of MFS, with an emphasis on what characteristics have contributed to their rapid widespread in

[7]Nearly 34% of the eligible population taking, at least one loan, within two years after eligibility.

the developing world. This section also describes the cellphone market in Haiti and the specific conditions or airtime loans in the country. Section 4 outlines out empirical strategy, and the data. Section 5 develops the econometric methodology. Section 6 analyzes the heterogeneity in people's responses to credit, focusing on the role of liquidity constraints and convenience. Section 7 concludes, and is followed by an Appendix.

2 Background

2.1 Mobile Financial Services

Since the early 2012, more than 50 billion dollars have been invested in the Financial Technology sector by adding digital options to existing financial products and by creating new services that appeal customers that the formal financial sector has struggled to serve (McKinsey, 2017). Financial technologies (FinTech) includes all the services that improve and automate the delivery of financial services. As part of the FinTech sector, Mobile Financial Services (MFS) includes products where mobile phones are an integral part of the user's experience. Depending on the service they provide, MFS can be divided in four categories: mobile money, insurance, savings, and credit.

Digital credit[8] allows subscribers to access short-term loans from a mobile device, with the whole application process processed remotely. It has several advantages over existing formal financial institutions that allow it to serve low income customers. It manages information asymmetries using non-traditional sources of data. By not relying on 'hard' data such as proof of income, employment or a formal credit histories, it can screen customers for which traditional services find difficult to asses their risk level. Additionally, the costs of services tends to be lower, in particular in remote areas, as digital products rely on the infrastructure already in place by cellphone companies. Furthermore, the digitalization of products can dramatically lower the wait-time of transactions that applying on physical locations and the manual sorting of applications entails.[9]

The risk profile of each digital credit product depends on how it combines alternative credit scoring, usage of mobile money to distribute funds, and the amount of collateral required. Consider

[8] Also called mobile credit and digital lending

[9] Several products deviate from one or more characteristics but are still part of the ecosystem.

three tiers of such products. The first tier, where airtime loans reside, involves the lowest level of risk exposure for providers. Products in this category leverage the cellphone's data-trail as a credit scoring system, with only a person's number as collateral. The loan can be used to make calls, send SMS or use the internet. The only consequence of defaulting a loan is that the customer loses the ownership of his cellphone number. Airtime loans present several advantages over other products that explain its rapid adoption in most cellphone markets. First, low risk makes them attractive for Mobile Network Operator (MNO) with no previous experience with credit products (GSMA, 2014). Second, they can be launched as a stand alone product that does not require the development complementary services, in particular of a network of mobile money agents with enough liquidity to manage large withdraws; a factor that several MNO have find challenging (Suri, 2017). Third, the product does not require a partnership with a financial institution, and tends not to be subject to regulatory approval. Although statistics are hard to come by, it seems that nearly every network operator that offers a prepaid service also offers at least one version of an airtime loan, with slight differences in the terms of the service and the size of the loans it makes available. While airtime credit products are not included GSMA's Mobile Money Deployment Tracker making difficult to obtain information of similar products around the world (GSMA, 2014), we have found at least one MNO offering a similar product in every market we surveyed in Latin American, sub-Saharan Africa, and Asia. It seems safe to assume that these popular financial products exist in every country in the world unless explicitly prohibited by law. Due to their popularity with MNOs and customers alike, airtime loans provide a ubiquitous first rung in the financial inclusion ladder for billions of mobile phone users who have never before had access to formal financial services.

The second tier consists on digital credit products that use formal credit histories and rely on bank accounts to disburse funds. These products are provided by traditional lenders that use mobile applications as a way to reduce frictions during the loan application process. Evidence suggests that the expedience of fund delivery has a detrimental effect on the repayment probability Bulando *et al.* (2020).[10] Additionally, the easier application process allows lenders that use digital

[10] The authors exploits that loan are disbursed in batches to identify the how longer delays affect loan repayment, finding that one additional hour of delay causes a 0.4 percentage points increase in the repayment probability. Since the usage of the funds is not observed, they are constrained on the mechanisms behind this finding. The results is not driven by customers, who wait the longest, repaying the loan with the funds just provided; an option that is

channels to charge a 'convenience' premium over their brick-and-mortar competitors that cannot be explained by differences in the cost of regulation or raising funds between different provider (Buchak *et al.*, 2018).

The third tier contains products that similarly to tier one rely on cellphone metadata to screen customers, but with the additional characteristic that loans can be converted into cash.[11] The first product of this kind was launched in Kenyan in 2012, and during the first two years of its existence made over 20 million loans, many for sums of a few dollars, to 2.6 million borrowers (Cook and McKay, 2015).[12] This higher-end digital credit products have experience a slower pace of adoption for reasons that include higher risk, the need to develop an ecosystem of services to support the product, and the fact that they need a partnership with a financial institution which makes them subject to regulatory approval. The cost of development and maintenance of these products can be large. As reported by Björkegren *et al.* (2020), there is evidence that customers strategically change their behavior to manipulate the algorithm in their favor, requiring constant updating of the credit scoring algorithm to avoid increments in the default rate.[13] Yet, as airtime loans prove the feasibility of providing uncollaterilized credit to customers, algorithms improve, and competitive pressure increases, we expect that MNO will become more conformable, and willing, to expand credit access using digital loans that can be converted into cash.

2.2 Cellphones in Haiti

Haiti is the poorest country in the Americas with a quarter of the population making less than 1.90 dollars a day (The World Bank, 2020).[14] In terms of phone ownership, the country lags behind the rest of the continent with only 60% of households owning a mobile device in 2018. Still, this represents a large increase from only 20% eight years before, and makes cellphones the second most

allowed. Loans are paid close to maturity independently of the waiting period.

[11] Some products use additional data extracted from a customer device that includes information on application usage.

[12] For a review of the state of the market in 2017 see Francis *et al.* (2017)

[13] We do not know of any evidence that customers change their usage patterns to get more favorable access to the airtime loans. This is not surprising given the relatively low stakes and the simple rule granting access to the product. We can not discard that customers defaulting an airtime loan do it strategically to get a new number soon after. However, the data suggests that the problem, if exists, is a minor concern.

[14] For comparison, the poverty rate in the Latin America region is close to 3.5% and has been on a downward trend for several years. In contrast poverty rate in Haiti has been stagnant for most of the decade (The World Bank, 2020)

commonly owned asset, only behind beds (72%), and above radios (52%), TVs (37%), and fans (20%) (FinScope, 2018). There is reliable cellphone service in the whole country, with operators offering additional services such as mobile money and airtime loans.

In a typical month, there are 3.5 million active subscribers.[15] As is the norm of the cellphone market in developing countries, the majority of cellphone customers are prepaid.[16] Postpaid plans are available but there are several reasons that hinder their adoption. First, they are expensive with lower end plans costing more than the monthly expenditure of 96% of prepaid customers. Second, they create a financial commitment that most households prefer to avoid given the volatility and uncertainty of their income. Finally, lack of proper documentation and financial information makes that most users would simply not classify for postpaid billing.[17]

Panel A in Table 1 shows summary statistics for a typical month of usage both for recharge and communication transactions. A key characteristic of prepaid plans is that they do not restrict the amount or schedule of recharges. As documented in other studies, payment flexibility induces a pattern of transactions characterized by small and frequent purchases of airtime, with recharges that tend to coincide with the timing of cash-payments, (Attanasio and Frayne, 2006; O'Donoghue, 2020; Jack and Smith, 2020). We observe a similar pattern with the median customer spending around 3.8 dollars in over eleven different recharges during a typical month. Individual recharges are small, with an average amount of only USD$0.30. Most customers are active everyday, and have, on average, 8 unique contacts in a regular week. This is a similar level of usage to what other studies report in the developing world, see Khan and Blumenstock (2016).[18]

[15]There is a large number of lines that are active for short periods of time. We focus on numbers that have been active for at least four consecutive months.

[16]As an example, Bharadwaj *et al.* (2019) reports that prepaid connections account for about 95% of total subscribers in India, as are 97% in Kenya, 98% in Tanzania, and 74% in Brazil.

[17]Acquiring a postpaid plan requires customers to approach one of the companies' offices and show proof of identification and financial documents. However, only 75% of Haitians have an official ID card. Once a customers is approved, he must leave a one-month deposit. Limited postpaid plans start at 1,800 HGT (25 USD), with more expensive plans ranging between 3,500and 5,000 HGT (50-70 USD) per month.

[18]An entry level postpaid plan costs around 25 USD, Figure 5 shows how this more than the monthly expenditures of 95% of active customers. Figure 2A shows that there is a strong preference for small and frequent recharges that takes place along the whole distribution of total expenditure.

Table 1: Network statistics: Active customers April 2019

Panel A	mean	std	1%	10%	50%	90%	99%
Recharge activity							
Total recharge (monthly USD)	6.98	15.77	0.0	0.45	3.9	15.23	50.14
Average recharge (USD)	0.55	1.01	0.13	0.17	0.32	0.96	4.43
Number recharges	14.21	15.61	0	2	11	30	61
Communication Traffic							
Contacts called per week	9.91	20.65	0.0	1.5	7.25	21.75	43.25
Days a week with activity	5.09	1.92	0	2	5	7	7
Total Calls	98.12	121.64	0	6	56	241	574
Total SMS	126.99	408.45	0	0	2	327	2072
Panel B: If used loan only							
Number of loans	2.9	2.6	1	1	2	6	13
Total amount borrowed (USD)	2.0	2.8	0.1	0.3	1.2	4.4	11.8
Share of expenses financed	0.28	0.2	0.02	0.08	0.24	0.52	1.05

Note: Includes customers that in April had been active for four consecutive months. Unless otherwise noticed, values correspond to month-aggregates.

2.3 Airtime loans in Haiti

In Haiti, most prepaid customers have access to airtime loans. The only eligibility restriction is that a phone number must have been in the network for four weeks, and report at least one recharge in the previous month. In practice these conditions make access to the product almost universal, with 97% of active numbers being eligible. Airtime loans are very popular with 40% of eligible customers requesting at least one loan each month; this percentage increases to 65% when considering loan demand over a two-month period. To understand the magnitude of the reach of the product, it is worth considering that 46% of the adult population does not have access to any financial service, with two out of three loans coming from informal lenders, friends, and family (FinScope, 2018). The high demand for airtime loans is intrinsically linked to high dependence on prepaid plans. When a customer runs out of balance, he cannot new initiate transactions unless more balance is added to the account. Finding places to recharge is not difficult, every street vendor offering recharges, as well as the possibility to buy airtime on formal shops, or electronically using mobile money or a web application using a debit card. On a typical day 89% of all recharges are made with street vendors and 8% and using mobile money.[19]

Loans can be requested directly from any handheld device.[20] When a customer requests a loan, the system provides a single loan offer that ranges between 0.13 and 2 dollars. Figure 1 shows most of the loan transactions are less than one dollar, with a median loan size of USD$0.39 dollars (mean USD$0.56). After accepting the offer, but before the loan is disbursed, the customer must read a menu that explain the loan conditions. The customer agrees to pay the loan principal and a 10% facilitation fee before thirty days. The total facilitation fee does not change in the case of early, or even immediate repayment. We only see transactions where a customer accepts these conditions. The total amount can be paid in multiple installments but the full amount must be paid before additional credit can be obtained.[21] As panel B in Table 1 shows, the median borrower takes two loans each month. This adds up to 1.2 dollars, or 20% of his total expenditure. The amount the system offers varies depending on the customer's recharge history and correlates with the average amount deposited in the past.[22]

The only effective collateral for an airtime advances is the customer's phone number. Focus groups we conducted among the working poor in peri-urban Haiti revealed just how attached people become to their phone numbers given the potential costs of changing numbers, including the disruption to one's social network. These costs increase the longer a person has own the number and when the number is used for work. Most loans are fully repaid in less than 5 days with a very low default rate, a result that seems to validate the high valuation people place on their numbers

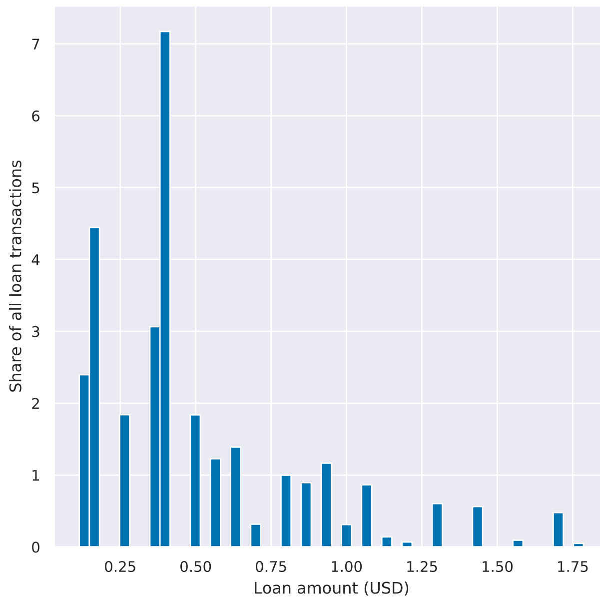
[19]Recharging using a mobile money account requires to have a positive balance. It is not possible to take Mobile Money loans.

[20]The system works both over Unstructured Supplementary Service Data (USSD) and a proprietary mobile app. USSD is an interactive, menu-based technology, supported on most mobile devices. It is similar to SMS with the main difference that messages travel directly to the mobile network provider, creating a two-way exchange of data between users and the network. An additional advantage is that it works on any phone without the need to install any app, or the need of mobile data.

[21]One exception is balance transferred from another customer. In the case that balance transferred is less than the principal plus the origination fee, the customer receives 80% of the amount sent, and the rest is used to pay the loan.

[22]In practice, there are two types of loans available. One credit line provides smaller loans that can be used in network-activity only, while the second can be used in any services. As they are accessed using the same platform, have the same service fee, and can be used simultaneously, we treat them as a single product. When requesting a loan, it is not necessary that a customer has zero balance. However, we observe that loan requests occur when balance is approaching zero. It is not possible to access to the precise algorithm that provides the loan offer. However, the loan offer is linear with the average recharge

Figure 1: Distribution of the amount of all completed airtime loan transactions
May and November 2019

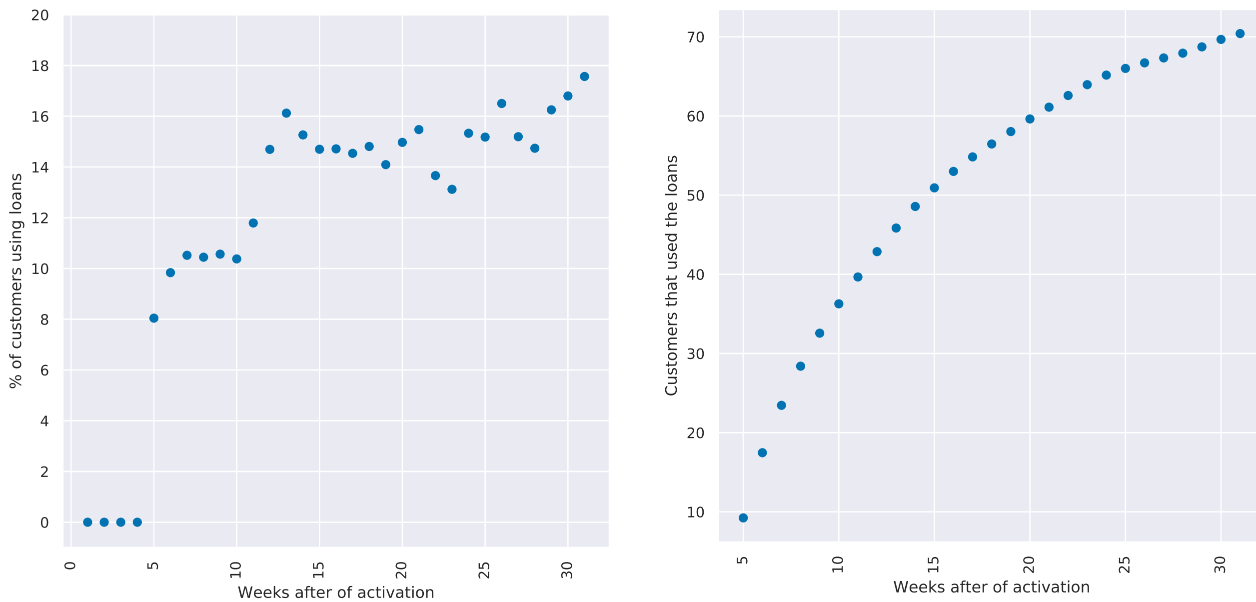


Note: Loan amounts are discrete values

that we found in the qualitative work. Revealing the popularity of airtime loans, Figure 2(a) shows that in the week they became available almost 8% of eligible numbers use the service. This percentage increases overtime, with the majority of customers using the loans, at least once, by the time they reach 30 weeks in the network, see Figure 2(b).

Figure 2: Loan demand by week relative to activation

(a) Percentage requesting loan (b) Cumulative usage



Note: New customers become eligible for airtime loans five weeks after activation. Includes only customers who were ultimately active for at least 7 months in the network.

3 Theoretical Model

In this section, we introduce a simple model to capture in a stylized manner the intra-day tradeoffs agents face between communication and food expenditure. A key feature of the model is that the demand for cellphone communication occurs at higher frequency than income (e.g., wage) payments. This feature introduces the possibility of an intra-day liquidity constraint (i.e., a mid-day cash crunch). When this intra-day liquidity constraint binds in the absence of a credit market, consumption decisions become sensitive to the timing of income. With this structure, the model is intended to reflect in the abstract the daily financial dilemmas faced by unskilled workers, day laborers and the self-employed in the informal economy, of which there are many in Haiti.

This model has two periods, which roughly correspond to mid-day and end-of-day. During the first period, $t = 1$, the agent has the possibility to consume cellphone minutes m_1, at a price of P, which provides utility of $u(m_1)$. Function $u(\cdot)$ is twice continuously differentiable with $u(0) = 0$, $u'(m_1) > 0$, $u''(m_1) < 0$ for all $m_1 \geq 0$. The total consumption of minutes during $t = 1$ depends on the cash-on-hand the agent has available, which we denote D. Additionally, to consume minutes the agent must recharge his balance account by visiting an airtime vendor. Finding a vendor distracts him from working by an amount of time e, representing a transaction cost of manually recharging one's airtime balance. While this effort cost depends on several factors, including the agent's location relative to airtime vendors and time of day, these are beyond the scope of this simple model. Similarly, we abstract from any uncertainty about this effort cost and, for simplicity, assume it is fixed at $\bar{e}$.

The second period, $t = 2$, represents the end of the working day when the agent receives his earnings and makes additional consumption decisions.[23] Total earnings equal $E(1) = \bar{E}$ if the agent does not spend time looking for an airtime vendor, and $E(1-\bar{e})$, with $E(1-\bar{e}) \leq \bar{E}$ if he bought airtime in $t = 1$. The agent consumes a bundle good c (e.g., food) for a price of P_c. The agent can consumer additional cellphone minutes, m_2, at the same price P. However, reflecting that during this period the agent is not working and has to acquire good c by going to the market, we assume there is not penalty for buying airtime. Utility from consumption of c is given by $v(c-\gamma)$ with $v'(m_1) > 0$ and $v''(m_1) < 0$ for all $c \geq \gamma$. The parameter γ reflects that the agent must guarantee a minimum consumption level, effectively making some consumers too poor to buy minutes.

Given this setup, the agent face the following intra-day maximization problem:

$$\max_{m_1, m_2, c} u(m_1) + \beta \left[u(m_2) + v(c-\gamma) \right] s.t. \tag{1}$$

$$Pm_1 \leq D \tag{2}$$

$$Pm_2 + P_c c \leq D - Pm_1 + E(1-\bar{e}) \tag{3}$$

[23] A more complicated model could include the agent receiving a fraction of his earnings discreetly over the day, or having uncertainty over the final value of his earnings.

A solution set m_1, m_2, c is such that:

$$\frac{u'(m_1)}{u'(m_2)} = \beta \tag{4}$$

$$\frac{u'(m_1)}{v'(c-\gamma)} = \beta \frac{P}{P_c} \tag{5}$$

$$Pm_2 + P_c c \leq D - Pm_1 + E(1-\bar{e}) \tag{6}$$

An interior solution is guaranteed by $P_c\gamma > D + E(1)$. We focus on that case since, otherwise, the agent is too poor to buy cellphone minutes.[24] In the case the solution to the maximization is not binded by condition 2 the agent has no need for credit markets.

In the absence of credit markets, an agent with limited cash-on-hand D is constrained in his consumption of cellphone minutes at $t = 1$, implying that the marginal rate of substitution between the consumption of minutes at $t = 1$ and $t = 2$ is larger than β, and $\beta \ \frac{P}{P_c}$ for the case of good c (conditions 4 and 5). In practice, this implies that an agent that starts with a low level of D would be better-off if he was allowed to borrow against his future earnings. The share of D over total income that determines when an agent is constrained depends on the relative prices of minutes, the price of good c, and the relative valuation of minutes consumed in the first versus the second period.

Airtime loans allow the agent to acquire unlimited balance in period $t = 1$ without the need to incur in the effort $\bar{e}$. By taking a loan, the agent agrees to pay in $t = 2$ the full amount plus a fee r: $P(1 + r)$. This makes minutes used in the first period more expensive and creates two sources that explain loan demand. For people that are constrained at $t = 1$ airtime loans allow them to equalize the marginal rate of substitutions between m_1, m_2, and c, leading to an increase in the total expenditure on cellphone minutes. Second, for agents that are not constrained in $t = 1$, the loan eliminates the effort costs associated with finding an agent. If the cost e is relatively large

[24] When $P_c\gamma \in [D + E(1-\bar{e}), D + E(1)]$ a solution with $m_1 = m_2 > 0$ and $c > 0$, as well as $m_1 = 0$ and $m_2 > 0$ $c > 0$ is possible depending on how large the cost e is. As we assume that e is relatively small, we rather focus on the case where $P_c\gamma > D + E(1)$.

compared with the increase in the cost of minutes, the agent finds more convenient to pay the cost of the loans instead of recharging through an airtime vendor.

We provide a simple example that shows the existence of these two effects. To illustrate this, we fix total income and vary the share that cash-on-hand at $t = 1$ represents of the total daily income.[25] A characteristic we impose on $u(\cdot)$ and $v(\cdot)$ to reflect the nature of the two goods, but that is not necessary for the solution of the model, is that $u'(x) << v'(x)$, implying that the marginal utility of an additional minute decreases fast compare with the marginal utility of additional consumption of food for the same level of expenditure, making the share of cellphone expenditure small.

When D is small, condition 2 is binding, making that the total amount of minutes consumed at $t = 1$ equals when $m_1 = \frac{D}{P}$. In this case, condition 4 no longer holds. This causes the agent to trade phone consumption in the second period for additional phone consumption in the first period. In Figure 3(a), we see that the total utility for an agent with the same level of total income, but that is not constrained in his purchase of m_1 (solid line) is higher than the constrained solution (dashed line). This leads to a consumption of minutes below what otherwise the agent would demand if he could borrow, see Figure 3(b).

When borrowing is allowed, we see that constrained agents increase their consumption of minutes by a large amount, also increasing their total utility. In models that conform to the canonical Permanent-Income Hypothesis, the timing income payment does not affect consumption decisions, and any increase in the credit limit should not generate significant changes in the debt level. This is not the case when the agent borrowing capacity is limited.

An agent who is not cash constrained at $t = 1$ will use airtime loans because of the convenience they bring by avoiding the need for looking for airtime vendors. Minutes become more expensive, but when the costs associated with recharging during $t = 1$ are large enough the agent prefers to take loan over the consumption bundle that is purely financed with the agent own resources. It is worth mentioning that in this case, the change in total consumption tends to be small because it is only driven by the transaction costs of recharging. If they were absent, a non-constrained agent would not use the loans. An additional channel that could induce demand for loans from unconstrained

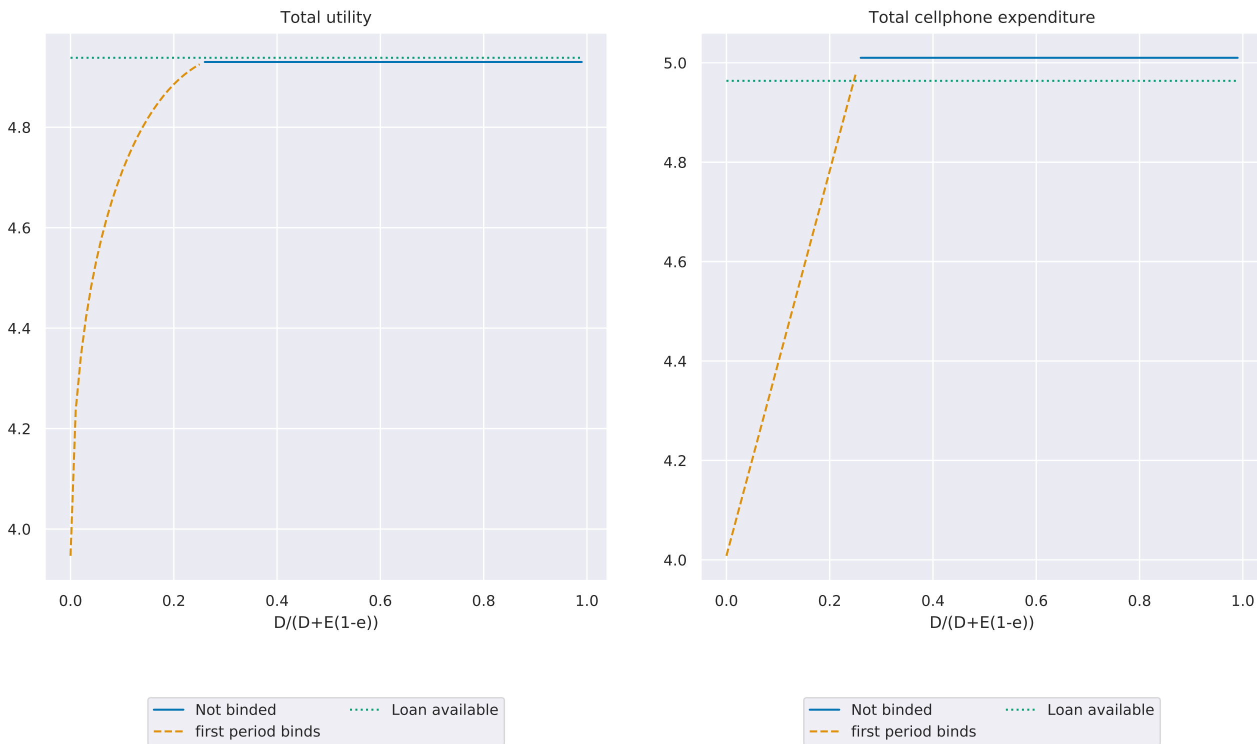
[25] As the searching cost of airtime vendors is a percentage of E, an agent that starts with a high D will have a searching cost as a percentage of his total income that is lower in absolute terms.

agents in the absence of searching costs is the presence of uncertainty on the second period earnings, as it can induce precautionary saving motives concerning the possibility that income might bind in the future (Gross and Souleles, 2002).

Figure 3: Utility and communication expenditure from the simple model

(a) Utility level

(b) Total phone expenditure



Note:

Finally, consider two simple extensions to this model. Without modifying the model to make these extensions, we discuss why they might make sense given our research question and how they might change the patterns in Figure 3. First, it would be reasonable to introduce heterogeneity in daily earnings that is correlated with cash-on-hand D (e.g., poor with low D and low E and non-poor with high D and high E). Obviously, this would amplify the effort costs associated with airtime recharges in $t = 1$ for the non-poor relative to the poor and, with it, the convenience of airtime loans for the non-poor. Second, to reflect the fact that many self-employed workers in the informal sector now rely on their phone to find and coordinate jobs, we could include minutes as an argument in the earnings function as well as in the utility function. This would naturally amplify the effect airtime loans have on crowding-in additional communication expenditure. These two extensions would only sharpen the core results of the model that access to airtime loans (i) prompts differential responses from the cash-constrained poor and the unconstrained non-poor and (ii) crowds-in additional communication expenditure for the former but not the latter.

4 Empirical Strategy

4.1 Identification

To identify the impact of credit access on cellphone expenditure and network behavior, we leverage the eligibility rule that grants access to airtime loans four weeks after a line is activated. This allows us to implement an event study design (Athey and Imbens, 2018).[26] Proper identification depends on several assumptions. The first is parallel trends in the absence of treatment. A weaker version of this assumption, that is more likely to be satisfied, only requires parallel trends conditional on covariates, see Callaway and Sant'Anna (2018). The second assumption is no anticipatory behavior. As stated by Sun and Abraham (2020), this is more plausible when participants do not have private knowledge about the treatment path that might change their behavior in anticipation of the treatment. In the setting we study, it is possible customers are aware that after a certain period they will have access to airtime loans. Evidence from other digital credit products shows customers are willing to take costly actions, like changing their network patterns, or buying pre-used a SIM card, to gain access to loans (Björkegren *et al.*, 2020). We argue that the value of airtime loans is sufficiently low to deter such behavior; a fact that the low default rate seems to support. Moreover, even in the case people increase their expenditure prior to eligibility to classify to larger airtime loans, our results would only under-estimate the true impact.

The final assumption imposes no variation across cohorts. These requires that each cohort

[26]This is a special case of a general Difference-in-Differences strategy that has been applied empirically to a wide range of contexts. Such designs are sometimes also referred to as Staggered Adoption Design (SAD). For a complete review of the studies implementing a similar methodology see Clarke and Schythe (2020)

experiences the same path of treatment effects, in particular, that the composition of individuals does not differs over time in characteristics that affect how they respond to treatment. Additionally, we need that the treatment effects are the same across cohorts in every relative period, that is, that the type and intensity of treatment does not vary due to calendar time-varying effects. Given that we rely on administrative-data, it is not possible to test for differences in the characteristics of the customers entering the sample each week. We argue, however, that once we center the analysis on customers that stay for a significant period in the network most of the differences between customers disappear.[27] The eligibility criteria and size of the loans does not change over the period studied, and any calendar effects that seasonality might introduced are controlled by their respective dummies.

As our objective is to understand changes on the levels of the transactions, we aggregate all entries for the same customer at a weekly level.[28] Working with data aggregated at the week-level has the advantage that it filters most of the noise created by both inter and within-day fluctuations. Additionally, aggregating each customer's transactions at a week-level facilitates the estimation, since the data in its original form has more than two billion entries. We first estimate a standard two-way fixed effects model as described by equation 7:

$$y_{i,week} = \alpha + \beta_1 Eligible_i + \mu_i + \lambda_{week} + u_{i,week} \tag{7}$$

Our main variable of interest is total weekly expenditure. This variable aggregates all the recharge transactions a person makes during the week using any of the recharge methods available. We also explore the impact of credit access on different network features that include the number outgoing contacts, average call duration in seconds, and number of outgoing interactions. We find that total expenditure is a better indicator of network behavior as people strategically changes how many people they call, how often, and for how long, in the presence of low balance. The estimates

[27] As described by Roth (Working Paper), restricting the sample to only customers that do not drop from the sample can induce selective survival bias. Our results are robust to lowering the inclusion criteria by allowing customers that drop early from the sample, see 5A

[28] Each week contains Monday to Sunday. Week of the year is defined according to the International Organization for Standardization (ISO)

for this and all subsequent models use standard errors clustered at the individual and week levels.

This model uses a single post-eligibility indicator $Eligible_i$ for all periods after airtime loans become available.[29] We also include μ_i and λ_{week} to capture individual and calendar-week fixed effects. As a control group, we include a random sample of well-established lines. Due to data limitations we cannot say precisely when these lines were first activated, but they were active at least five months before the period we study. We chose a random sample twice as large as the number of lines that we observe as treated, we implemented several tests and our results are robust to the size and the sample draw for the control group. The eligibility of these phone numbers does not change during the period studied and they act as a counterfactual. Additionally, including these numbers allow us to properly estimate the calendar week fixed effect.

A growing literature shows that in case there are heterogeneous treatment effects results from equation 7 are problematic as customers who are treated first receive a larger weight in the coefficients, with the weights depending on the size of each treatment unit, and the number of periods treated (Goodman-Bacon, 2018).[30] To account for this, we also estimate a model with coefficients for each week a subscriber in the sample:

$$y_{i,week} = \alpha + \sum_{j=-4}^{-2} \beta_k (Lag\ j)_{i,week} + \textstyle\sum_{k=0}^{7} \gamma_k (Lead\ k)_{i,week} + \mu_i + \lambda_{week} + u_{i,w} \tag{8}$$

Lag and lead are dummies defined with respect to the number of weeks a number is from gaining access to airtime loans. We identify the fifth week after activation as week zero and define the lags and lead accordingly. As the notation shows, we omitted the lag for the week before a customer became eligible. It is common practice to use the first lag as baseline. However, we decided to use the last lag because the first week of activity tends to be noisy and not to represent the activity levels in the following three weeks. The eligibility rule only allows us to observe a numbers' activity during four weeks before access to the loans is granted. As numbers can be activated during

[29]As the first week in the network is very noisy, we only use weeks two to four to estimate the baseline of the pre-eligibility indicators.

[30]Goodman-Bacon (2018) shows that the difference-in-difference estimator is a weighted average of all 2x2 estimators in the data, This makes that this estimator can easily change between specifications as controls can induce additional identifying variation.

any week of the year, this event takes place at different dates depending on the calendar-week of activation. The limited window of pre-loan eligibility also drives our decision to measure impacts only eight weeks after loan access is obtained; therefore each new customer is in the sample for only twelve weeks.

For completeness, we implement as a robustness check, two additional specifications. First, we implement a simple event study design where we do not include the random sample of well-established subscribers as a control group. Second, we take advantage of our relative large sample and use the subscribers that joined the network during calendar weeks 18 to 21 as a control group for the new subscribers entering the network during weeks 20 to 30. During this period, the eligibility status of the control group does not change. Results for key variables under the two additional specifications are provided in section 8.1, and are qualitatively the same as in our preferred specification.

4.2 Data

For this study, we used an anonymized database from the largest cellphone provider in Haiti, between January and December 2019. For each transactions, we observe the day, time and duration, as well as the cellular towers that connected the subscribers. Additionally, for each subscriber we have a daily register with information containing the time and amount of airtime purchases, balance transfers, and airtime loans usage. Similar data have been previously used to study population movement (Gething and Tatem, 2011; Lu *et al.*, 2012; Zagatti *et al.*, 2018), risk sharing in the face of natural disasters (Blumenstock *et al.*, 2016), and forecasting socioeconomic trends (Blumenstock *et al.*, 2015; Frias-Martinez *et al.*, 2013).

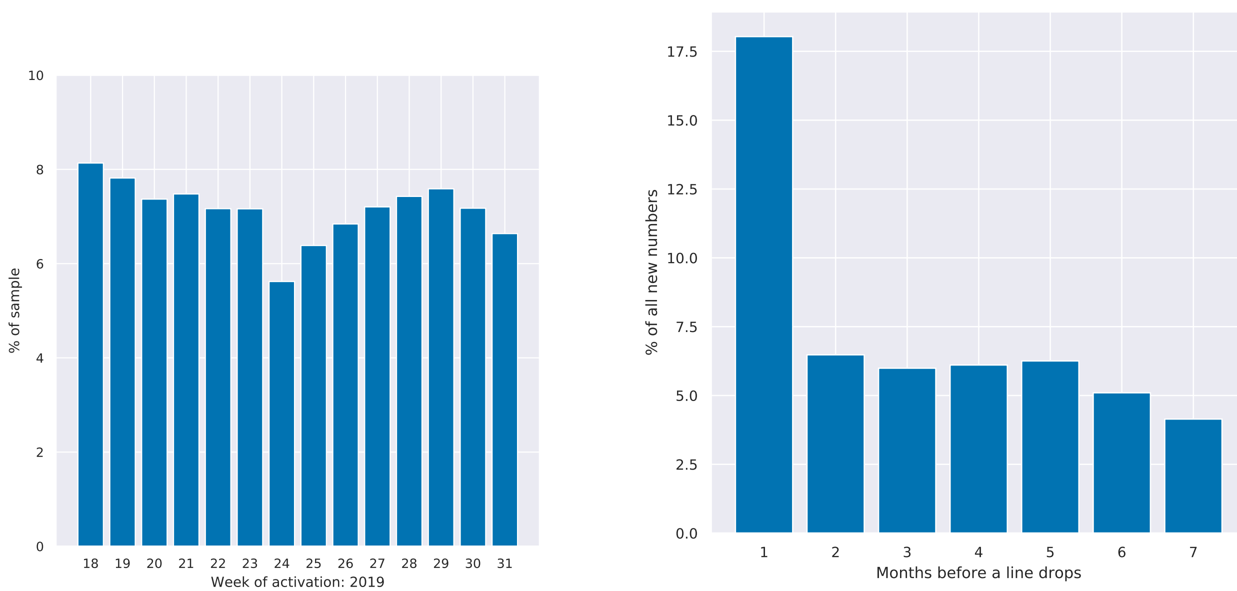
We aggregate the transactions of each customer at the week-level. This makes that, in calendar-year terms, our data covers week 18 to 48 of 2019. To observe how network behaviour changes before and after access to the airtime loans, we focus on new lines activated between May and July 2019 (calendar week 18 to 31), and follow their activity until the end of November of the same year (calendar week 48). During this period, a total of 278,697 new lines were activated, with new number entering the sample at a relative constant pace (Figure 4a). In the Appendix, Figure 1A shows the data coverage in terms of calendar-weeks in 2019.

Similar to the experience in other settings, there is a large level of subscribers churn (Roessler *et al.*, 2018). Only 39% of the lines activated during this period remained active when our records stop. We call these lines the long-term customers. The largest attrition occurs during the first month, when almost 18% lines stop registering activity. After this initial drop, attrition continues at a slower pace over the following months (Figure 4b). Customers that stop using their numbers are free to obtain a new number without any penalty, however, the eligibility condition still imposes a waiting period of four weeks before the new number can obtain loans.[31] We do not find evidence that a number dropping from the sample correlates with having outstanding loan balance.

Figure 4: New lines
May and July 2019

(a) Percentage of new lines during the period

(b) Attrition over time



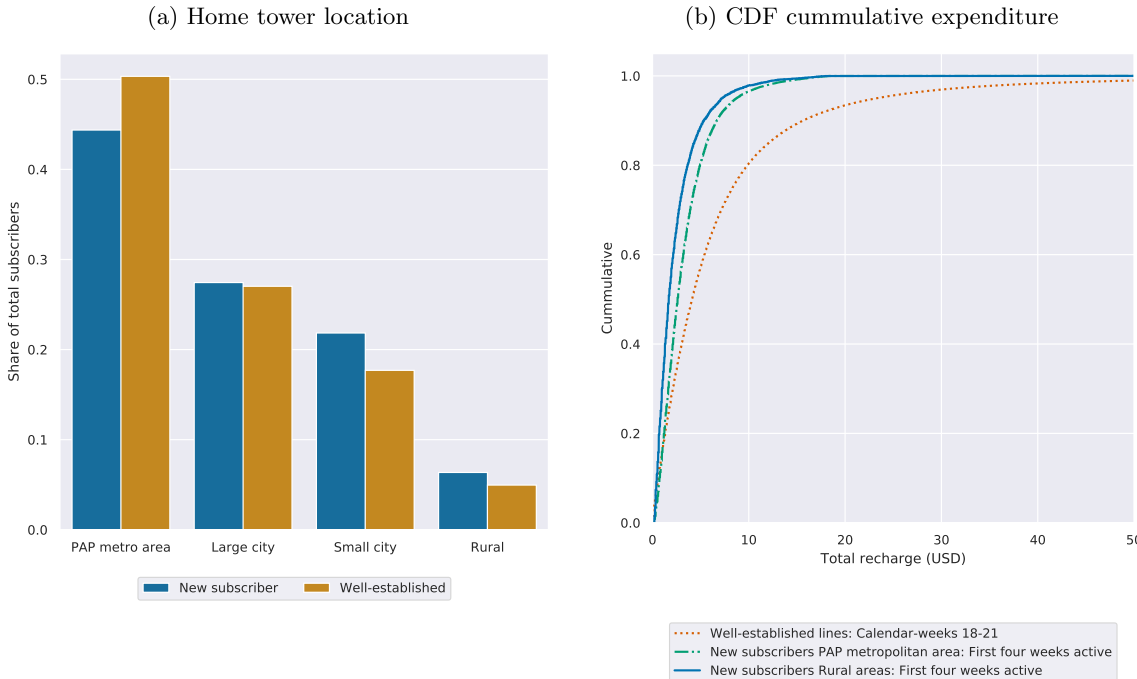
Note: Week of activation makes reference to the calendar-year. Week 18 corresponds to May first.

[31] A customer losses ownership of the number if he does not recharge during four consecutive months; in that case, the number can be reassigned. We assign as the last date we stop observing transactions as the day the line was dropped. One additional group that we identify are lines that we classified as sparse activity but still active (10%). These lines have gaps in activity for more than four weeks, but then register additional activity so it is not possible to classify them as inactive numbers, see Figure 3A.

We do no have personal information to compare the individual characteristics of subscribers in the long-term customers group with the set of well-established lines. However, evidence suggest that early adopters of cellphone technology are male, concentrated sector of the urban areas with higher income. Based on this, we should expect that the marginal new customers belongs to less favored groups. From the administrative data we see that, in fact, new lines have a slight higher probability to be locations in rural areas and outside the Port-au-Prince metropolitan area (Figure 5(a)). Still, phone subscribers are concentrated in the metropolitan area of the capital, where 65% of lines are located but only 37% of the population live, see Table 1A for details. Additionally, we observe that the total expenditure of the long-term customers is systematically lower than for the whole universe of well-established line (Figure 5(b)), a pattern that suggests that early adopters represent a wealthier segments of society.[32] We add a longer discussion on who new customers are with respect of the overall network in section 6.1, and account for differential effects by location as a robustness check in section 8.2.

[32]For reference, new subscribers in the top 10% of the expenditure distribution are below the expenditure of the top 10% of well-established lines (Figure 6A).

Figure 5: Key network metric activities
Long-term customers



Note: Well-established lines includes numbers that were active at the time when data first became available and remained active during the period of study. Total expenditure includes the calendar weeks 18 to 21 during 2019. New subscribers includes long-term customers only. Location was assigned using the tower that managed most of night activity of each subscriber.

5 Results

We start by showing the results from equation 7. Table 2 shows the impacts in monetary and as a percentage change with respect to the baseline values before loan availability. Loan access increased the expenditure of new subscribers in 15%. The additional expenditure comes with a marginal increase in the number of recharges, form an average of 2.6 to 2.8 recharges per week. In terms of network activity, it is difficult to point at a single metric that explains the additional expenditure. Overall, results can be summarized as subscribers having shorter, but more frequent interactions, with little effect in the number of unique contacts. Specifically, after eligibility the average customer makes 3.7 more calls, but average duration falls in almost 3 seconds.

Table 2: Impacts credit access
Post-eligibility period

	Expenditure (USD)	Average recharge (USD)	Number of recharges	Outgoing contacts	Outgoing transactions	Average call duration	Gambling expenditure (USD)
Baseline	0.92	0.31	2.58	6.74	41.07	74.93	0.01
Effect	0.15***	0.01***	0.19***	0.13*	3.72***	-2.65***	0.0
Δ in percentage	16.07	3.51	7.52	1.97	9.07	-3.53	1.33

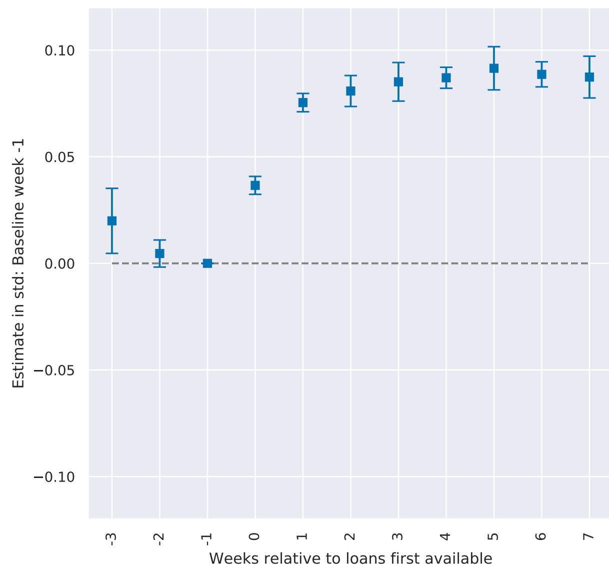
Note: Monetary values are provided in Haitian gourdes. The effect variable shows the results of a difference-in-difference where the pre eligibility period includes the three weeks before eligibility and the post period the 7 weeks that follow.

Unless explicitly noted all the graphical results we present in this section are in terms of standard deviations of the dependent variable, and come from estimating equation 8. We find that loan access increases weekly expenditure in a magnitude equivalent to 0.09 standard deviations, a magnitude that is in line with the aggregated result that we provide in Table 2. This impact starts in the week after loans are available and reaches (and maintains) this level by the second week after customers are eligible (Figure 6). Figure 7 provides an overview of the key network metrics. The patterns present large variation before and after eligibility. These results hold when we also include in the sample numbers that dropped 3 months after they were activated (Figure 5A)

One of the concerns with respect to the expansion of digital credit is that it can fuel the demand for gambling. This concerns is particularly valid in Haiti gambling is extremely popular.[33] There is not official data on the number of player. We find that cellphone records register that around 33% of subscribers gamble using their phones on a typical month. However, we do not find that access to airtime loans affects in a significant way the amount or frequency of lottery playing.

[33]There is not an official register of how many Haitian regularly gamble. However, it is telling that more than $1.5 billion dollars are spent per year, and it lottery stalls are a easy to see in most streets, with over 35,000 independently owned lottery stalls in the country Bhatia (2010)

Figure 6: Total weekly expenditure



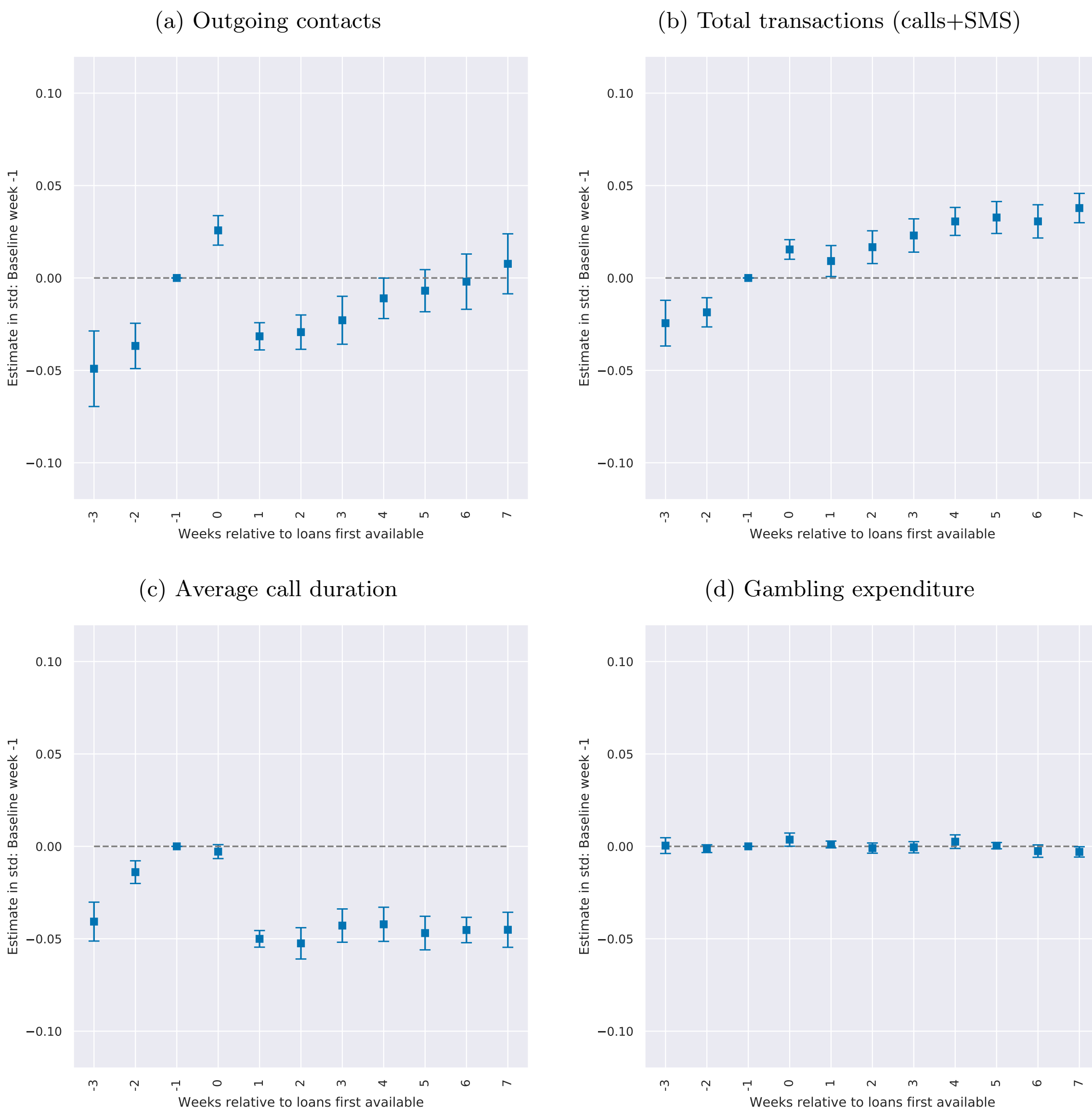
Note: Includes only long-term customers. Loan access is provided at week 0 and the week before is used as baseline.

Results suggest that access to credit crowds-in additional expenditure. Loan fees only account for 1% of total weekly expenditure, with the loan's principal financing 5% of total expenditure in the week airtime loans become available, and 12% a couple of weeks later (Figure 8). To provide a definite answer on the welfare effects of this result, it would be necessary to have information on the return to calls financed by loans, the effect on consumption of other goods, and the extend that airtime loans replace or complement other credit sources. We lack the data properly answer this question. However, as overall expenditure increases over several week, this is indicative that there must be a reduction in consumption of other goods, or in the levels of savings.

The pre-loan transactions we observe are the equilibrium result between the need for cellphone usage and each customer's capacity to prepay for the service. To explain why credit access increases total expenditure in a magnitude above repaying the loan's fees, three mechanisms can be at play. First, credit access relaxes binding liquidity constraints. As loans are quickly repaid and overall expenditure increases, these effects are consistent with subscriber perceiving the value of holding cash, and not spending in airtime, as high. This can be the case for poor individuals that depend on the informal economy and earn a living during the day, making them extremely sensitive to the timing of their income. Second, airtime loans introduce a behavioral component that affects the salience of the costs of calls as they eliminate the need to pay upfront for airtime using cash. From a theoretical perspective, a sophisticated but present-biased agent has incentives to limit the amount of airtime balance available at any given time to prevent future self from over-consuming. (Laibson, 1997; O'Donoghue and Rabin, 1999). By allowing instantaneous access to airtime, this self-control mechanism embedded in prepaid disappears. This mirrors the impact of switching to prepaid electricity billing, where the change led to a reduction of total consumption as it made explicit the cost of electricity for those consumers that switched (Jack and Smith, 2020).[34] A third mechanism is that the transaction costs of looking for a vendor during certain times of the day are perceived as very high, deterring a subscriber from recharging even when he has cash available. Under this mechanism, access to credit eliminates the cost of finding an agent and allows customers to modify their recharge patterns across the day towards times when they find it more convenient.

[34]The literature that explores the expenditure patterns of the poor also finds storage costs as a limiting factor on keeping large airtime balances (O'Donoghue, 2020). This does not apply as airtime take a month to expire, and can be transferred to other subscribers or renewed.

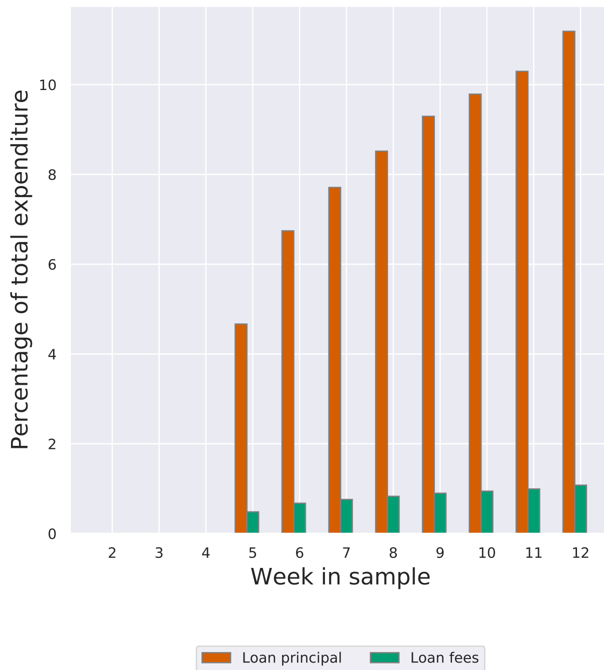
Figure 7: Key network metric activities
Long-term customers



Note: Includes only long-term customers. Loan access is provided at week 0 and the week before is used as baseline.

Of course, there is no reason to believe that a single mechanism should serve to explain the behavior of all individuals, with these channels not being mutually exclusive, and have different welfare implications. To understand better what mechanism is at play, in the next section we explore how income levels change the impact of credit access.

Figure 8: Share of total expenditure financed by loans



Note: Includes only long-term customers. The x-axis shows the number of weeks a customer has been active.

6 Heterogeneous Effects

While average impacts are important, they do not reveal the full extend that each mechanism plays to create the result we previously described. In this section, we provide empirical evidence of the extend cellphone consumption of poor and non-poor consumers changes as they gain access to credit. As our main analysis relies on administrative data, we do not have a direct measure of the financial conditions or daily cash flows of each customer. To circumvent this limitation, we take a two-step approach to test for differential responses to credit access accross the income distribution. First, we show that total airtime expenditure correlates with income level, an stylized fact that multiple studies have corroborated (Gutierrez *et al.*, 2013; Blumenstock *et al.*, 2015; Blumenstock, 2018). For this, we use a phone survey where participants granted us permission to link their cellphone records with their answers. Second, we divide customers by terciles depending on their pre-eligibility expenditure to create three groups: Low, Medium and High initial expenditure. Our key assumption is that income status (and financial constrains) improves, on average, with total cellphone expenditure. Results show that poorer customers in the lowest tercile of initial expenditure more than double their mobile communication spending when airtime loans become available, while access to loans leaves expenditure of the highest tercile unchanged. These pronounced differences exist despite relatively uniform patterns of loan usages between the two groups.

Mapping our results to the mechanisms we described before, we find suggestive evidence that poorer customers appear to use loans to relax liquidity constraints at critical communication times whereas non-poor customers primarily use loans for their convenience, as it gives them more discretion in when to visit airtime vendors

6.1 Income level and cellphone expenditure: A simple approximation

Several studies show that it is possible to predict individual socioeconomic indicator using the data-trail created by cellphone usage. These applications are useful to obtain economic indicators in data-poor setting, and to update existing data at a lower cost.[35] These applications rely on statistical methods to detect a relation between a socioeconomic indicator and cellphone usage patterns.[36]

There are still several open questions about how to best exploit cellphone records and the properties of the predictive models. Two concerns stop us from using these methods to predict

[35] A regular LSM survey requires the National Statistical Institutes to hire and train a large numbers of enumerators. An expensive task relative to the budget of emerging countries.

[36] These patterns include, among other, the number and average size of recharges, the of number of calls, the reciprocity of the calls, and the average distances travelled by citizens (Frias-Martinez *et al.*, 2012; Gutierrez *et al.*, 2013; Blumenstock *et al.*, 2015; Blumenstock, 2018). State of the art models do not depend on a single variable, and in several cases the use feature engineering to create features that can not be easily interpreted. Due to widespread data limitations Haiti has a long history in the usage of these methods. In the past, cellphone Detail Records, similar to the ones we use, have been helpful to understand the impacts of natural disasters on population displacement (Gething and Tatem, 2011; Lu *et al.*, 2012; Zagatti *et al.*, 2018)

each customer individual income status. First, these methods relatively long series of retrospective cellphone data.In order to implement these methods using individual predictors, it is necessary to be able to link individual characteristics of subscribers with their own cellphone metadata. A process that, by law, requires that the number owner agrees. In our case, the eligibility period provides a window of only one-month to collect the survey. This makes that the length of cellphone metadata is very short, with most applications using at least six months. Second, it is not know how fast a model's predictive capability decays over time, and when it is applied to a different sample on different time periods. Considering that our sample enters the network at different points, this raises several concerns about the impact of calendar-effect and the out-of sample validity of a model calibrated in a sample months in the past. Fully addressing this concerns is out of the scope of the current document.

We opt for a simpler approach where we show that total airtime expenditure maps with the observed income level. Other studies show that this relationship exists, even if it is not as predictable as machine learning methods (Gutierrez *et al.*, 2013). We use a phone surveys with 600 respondents that are representative of the universe of mobile money users.[37] As part of the informed consent process, we received authorization to link their answers with the mobile phone transaction database. We match survey answers to each participant cellphone records during the four weeks prior the survey in order to capture both weekly and monthly communication patterns.[38]

The majority of participants were male and head of their households (61% and 55% respectively), and had higher wealth levels than the average Haitian. Still, we observe high levels of food insecurity, with 61% reporting skipping meals or reducing portion sizes. Revealing the potential of MFS, all of them had a mobile money account but only 10% any type of banking product. Demand for airtime loans is high, with only two people not using the product in the 30 days before the survey. This makes that, as a form of credit, airtime loans are used with a higher frequency than other credit

[37]The information was collected in July 2019 as part of a related project. The universe of mobile money holder is 939,315. Restriction on the levels of activity and time in the network left us with a sample of 36,879 potential subscribers to survey. Two levels of compensation (50 and 150 HGT) in the form of airtime were offered as a participation incentive. We do not find evidence that the response rate was different depending on the compensation level.

[38]By using a shorter period, we run the risk of omitting the recharges of consumers that recharge a single large deposit per month.

product, with less than half of participants owning money to other sources. Descriptive statistics on the survey participant characteristics are shown in Table 2A.[39]

Only for those employed we have information about their income during the week. For this group, we estimate equation 9 to understand how income correlates with total cellphone expenditure, average amount and number of recharges. Total cellphone expenditure and the average size of recharges increase with the reported income, while we do not see any effect in the total number of recharges (Table 3).[40]

$$y_i = \beta_0 + \beta_1 ln(income)_i + \beta_2 age_i + \beta_3 men_i + \beta_4 Household\ Head_i + \beta_5 Day\ survey_i + u_i \qquad (9)$$

Table 3: Network transactions and income stability
Phone survey sample

	Recharges		
	Total Recharge (USD)	Average recharge (USD)	Number of recharges
ln(income)	7.74***	17.58**	1.29
	(2.64)	(7.49)	(0.97)
Household head	6.06	20.02**	-2.42
	(4.68)	(9.34)	(2.52)
gender	4.8	-8.87	6.06***
	(5.86)	(14.47)	(1.94)
age	0.09	0.45	0.05
	(0.27)	(0.56)	(0.11)
const	-43.75**	-73.35	13.17
	(21.42)	(61.53)	(8.66)
Observations	306.0	306.0	306.0
R2	0.07	0.07	0.08
Adjusted R2	0.02	0.02	0.03

*p<0.1; **p<0.05; ***p<0.01
Note: Includes only respondents that had labor income in the week prior to the survey.

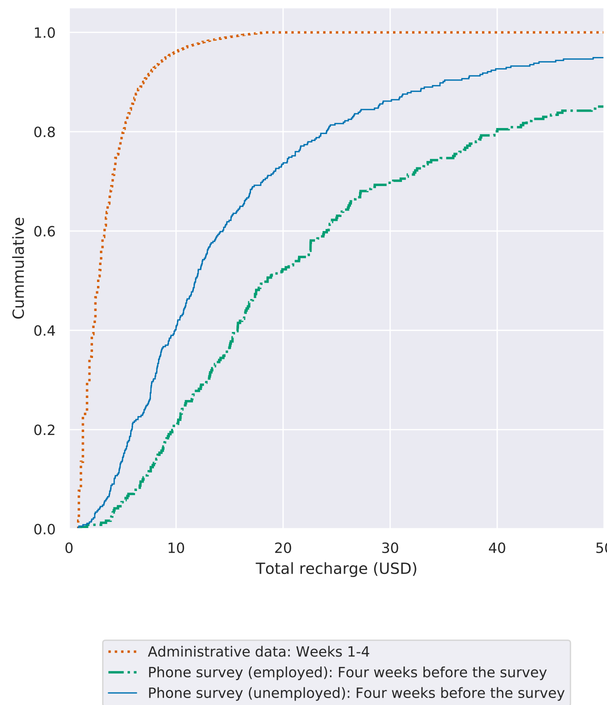
To show how cellphone expenditure levels compare between the survey and the administrative data, Figure 9 shows the cumulative distribution of total expenditure for the long-term customers

[39] With the exception of bank loans, most people have debts that are less 2 dollars, and amount that is not far from the credit provided by airtime loans. However, for debts owed to family and neighbors less than 5% accrue interest

[40] A similar story can be seen in Figure 9A, where we see that the recharge terciles map to higher levels of income and larger average recharges. We also checked the relation between income stability and income. We find that people with more predictable income spend more on their cellphones, both in total and per recharge (Table 3A)

and the participants in the phone survey. Reflecting that the survey sample contains wealthier individuals, we find that its expenditure distribution is to the right of the overall administrate sample. Two reasons explain this. First, the sampling process was done on mobile money users, a population that several studies show tend to be younger, more urban, and wealthier (Khan and Blumenstock, 2016). Second, the survey sample contains more well-established lines that tend to have higher levels of expenditure.

Figure 9: Cumulative distribution of total expenditure
Long-term customers and surveyed sample



Note: Administrative data contains only long-term customers. Weeks 1-4 represent the first month after activation when airtime loans where not available.

6.2 Heterogeneous effects of airtime loans

We explore the role of economic status on creating heterogeneous responses to credit access. As we do not have economic information for all the individuals in the cellphone transaction data, we leverage the discussion in the previous subsection and divide customers into three groups depending on their expenditure in the four weeks before airtime loans were available. Under the premise that expenditure levels reflect economic capacity, we proceed to explore how access to credit affect customers in a differential manner. Table 4 shows that there are important differences in the expenditure levels between the groups, with the median person in the high expenditure group spending five times more than the median customer in the low-expenditure category.[41]

Table 4: Total Expenditure before loans are available (USD)
Long-term customers

	count	mean	std	min	25%	50%	75%	max
Low Expenditure	32,598	0.89	0.40	0.13	0.58	0.91	1.23	1.56
Medium Expenditure	32,027	2.40	0.52	1.56	1.95	2.34	2.82	3.38
High Expenditure	31,717	6.11	2.89	3.38	4.09	5.13	7.01	18.56

Notes: Includes all the recharge transactions during the first four weeks. As we use terciles of the total expenditure the number of people in each group is very similar.

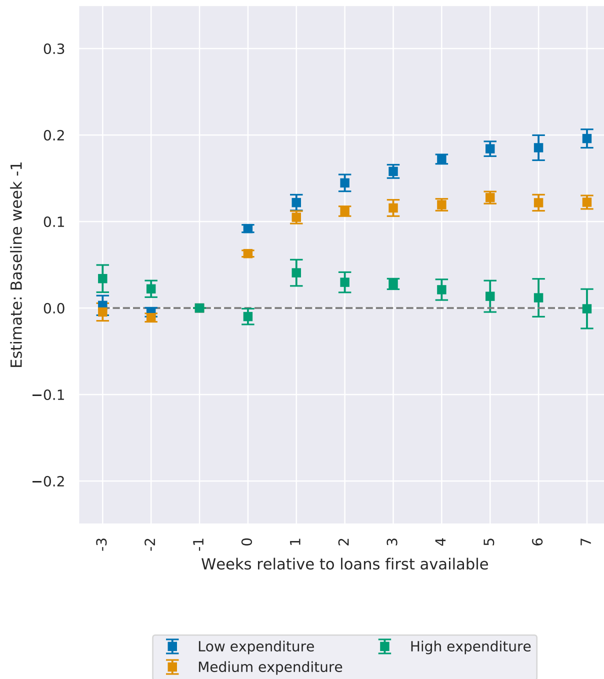
Estimating equation 8 for each individual group reveals a high heterogeneity of impacts. Results show that for low expenditure group, credit access leads to a large increase in total expenditure and sizable growth in the level of network transactions. The increase in expenditure takes place soon after loans became available (Figure 10). Weekly expenditure more that doubles, with individuals in this group spending, on average, 1.4 times more each week, gaining one more contact and making fourteen more transactions.[42] Similarly, the group with in the second tercile of initial expenditure experienced an increase of 30 percent in their weekly expenditure, see table 5. In contrast, people in the high expenditure group maintains similar levels of expenditure and we observe little difference in their level of network transactions. Still, the expenditure and level of transactions of the low expenditure group remains below the levels of more affluent groups, see Table 5.[43] We do not find that the location of subscribers significantly affects the magnitude of our results (Figure 14).

[41] Total expenditure also presents differences in terms of the average amount of airtime bought in each group. As in (Gutierrez *et al.*, 2013), we find that people with higher levels of expenditure tends to make larger average transactions (10A).

[42] In monetary terms, the total weekly expenditure went from 0.20 to 0.55 dollars.

[43] Figure 7A shows estimations at the week-level for key network variables.

Figure 10: Heterogeneous impacts
Total weekly expenditure



Note: Includes only long-term customers. Loan access is provided at week 0 and the week before is used as baseline.

These differences exist despite the groups having relative uniform patterns of loan usage. Specifically, loans only finance 9% of the expenditures of the low expenditure group, two percentage points more than the share financed for the group with a higher initial expenditure (Table 6).[44]

[44] Table 4A shows the share of total expenditure financed with loans each week. For details on the probability of borrowing each week see Figure 4A in the Appendix.

Table 5: Heterogeneous impacts

	Low expenditure			Medium expenditure			High expenditure		
	Baseline	Effect	Δ in percentage	Baseline	Effect	Δ in percentage	Baseline	Effect	Δ in percentage
Expenditure (USD)	0.22	0.33***	148.77	0.63	0.24***	38.13	1.62	-0.0	-0.26
Avg. recharges (USD)	0.14	0.07***	49.79	0.25	0.03***	10.42	0.47	-0.03***	-6.82
Number of recharges	0.95	0.74***	77.7	2.48	0.2***	7.93	4.02	-0.27***	-6.7
Outgoing contacts	4.39	1.2***	27.42	7.16	-0.3***	-4.12	8.62	-0.61***	-7.13
Outgoing transactions	17.25	14.2***	82.32	40.59	3.01***	7.41	62.19	-5.34***	-8.59
Avg. call duration	57.92	2.41***	4.17	77.68	-6.52***	-8.39	89.13	-5.67***	-6.36
Gambling expenditure (USD)	0.0	0.0***	54.25	0.01	-0.0	-3.48	0.01	-0.0**	-7.88

Note: Baseline levels show the average weekly expenditure during the three weeks prior to access to credit and compares it with the average outcome in the eight weeks that follow.

Table 6: Loan demand by group

	Borrowed	Average weeks with loans	Total loans	Average expenditure financed
Low Expenditure	0.45	2.46	3.31	0.09
Medium Expenditure	0.43	2.26	2.77	0.08
High Expenditure	0.41	2.26	2.73	0.07

Note: Groups were defined using the terciles of total expenditure in the four weeks before eligibility. Only long-term customers.

The previous results show that for the group with a low initial expenditure access to credit acts as a catalyser for additional expenditure, a result that we suggest exists as subscribers in this group often lack the necessary liquidity to pay for their calls up front. On the other hand, people with higher levels of income have a similar demand for loans but their total expenditure remains unchanged. We argue that the reason we do not observe an increase in expenditure is because people in the high expenditure group rely on airtime loans because of their convenience factor, as it allows them to visit airtime vendors when they find it more convenient.

6.3 Heterogeneous Motivations for Using Airtime Loans

We revisit the mechanisms that explain how credit access increases cellphone expenditure. Our results are inline with the existence of a liquidity constrain for poor customers. We observe a large increase in the expenditure levels of this group once airtime loans become available, allowing them to finance their cellphone expenditures. In the context we study, it is not surprising that large imperfections in the credit market exists. This makes consumption patterns extremely sensitive to the cash available at any point in time, a sensitivity that increases via precautionary savings in the cases when, in addition, there is uncertainty on future income. We cannot discard that, to some extend, people in this group are also affected by a reduction in the salience of the costs of calls. However, given the magnitude in the increase of expenditures, and that it lasts for several weeks, we believe this second mechanism is marginal, with the main impact of airtime loans being on reducing the extend liquidity constrain limit cellphone expenditure.

In contrast, subscribers with higher income have a similar demand for loans but do not change in a significant way their total consumption. We argue that this group suffers lower levels of short-term liquidity constrains, and that their usage of airtime loans is driven by a convenience factor. To understand the role convenience on credit demand, we explore for changes in the recharge patterns across the day. For this, we build on the fact that we are able to observe the precise timing of every recharge transactions.

We think of convenience in two different ways. The first one takes place during after hours at times when it is difficult to find an place to recharge. The second way we approach convenience is when finding agents is not difficult but the agent considers it inconvenient, and even when it has enough cash to recharge, he prefers to rely on airtime loans.

With respect to the first type of convenience, we find that when recharging opportunities are low, the volume of airtime loans with respect to recharges reaches its peak.[45] This takes place between midnight and six in the morning, a time where street vendors, who manage almost 90% of recharge transactions, are difficult to find. This pattern is mirrored by poor and non-poor customers

[45]Loan and recharge transactions follow a similar pattern across the day. In both cases, the share of transactions is relatively constant between 7am and 6pm with a spike to its highest levels during the next three hour. This results holds for costumers in any of the three terciles of initial expenditure (Figure 11A panels (a) and (c).

without statistically significant differences between the two groups (Figure 11B and D).[46]

The second, and more interesting, type of convenience is when airtime loan are used to strategically change the recharge pattern. We test for differential changes in hourly recharge patterns between poor and non-poor consumers. For this, we exploit the high frequency of our data to construct a dataset that indicates, for each day and hour, if a subscriber recharged. We estimate changes after customers become eligible using equation 10.

$$
\begin{aligned}
recharge_{i,day,hour} = \alpha + \sum_{h=1}^{24} \beta_h hour_{i,day} + \gamma Eligible_i + \sum_{h=1}^{24} \beta_h hour_{i,day,hour} \times Eligible_i + \\
\mu_i + \lambda_{week} + u_{i,day,hour}
\end{aligned}
\tag{10}
$$

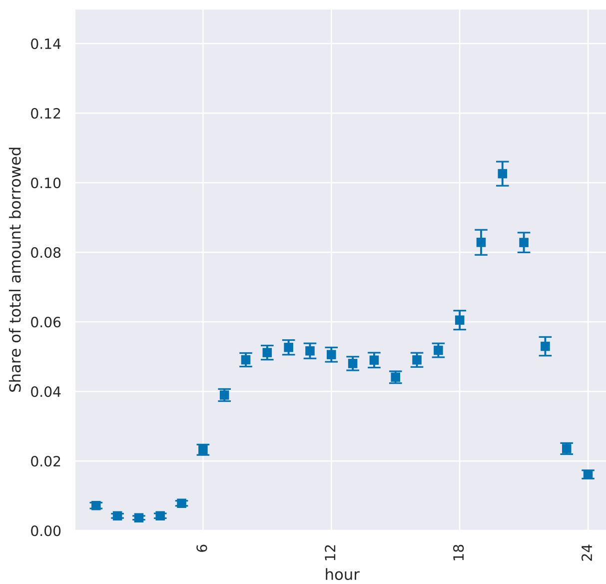
Our coefficient of interest is the interaction between the hour dummy and the indicator if a customer is eligible for the credit product.[47] To understand the results from Figure 10, it is important to remember that airtime loans eligibility reduces the number of recharge transactions for the non-poor, with the opposite effect on the poor. Moving to Figure 10, we see that the reduction in the number of recharges for the non-poor is particularly marked in the recharges that happen after 7pm, a time of the day when it is more likely that the transaction costs of recharging are higher. Poorer customers, on the other hand, increase their expenditure during those hours. A results consistent with the idea that, poor customers, who more likely to only have certainty over their daily incomes at the end of the day, wait until then to decide how much to recharge.

[46] Figure 12A presents the same results but by number of transactions per hour

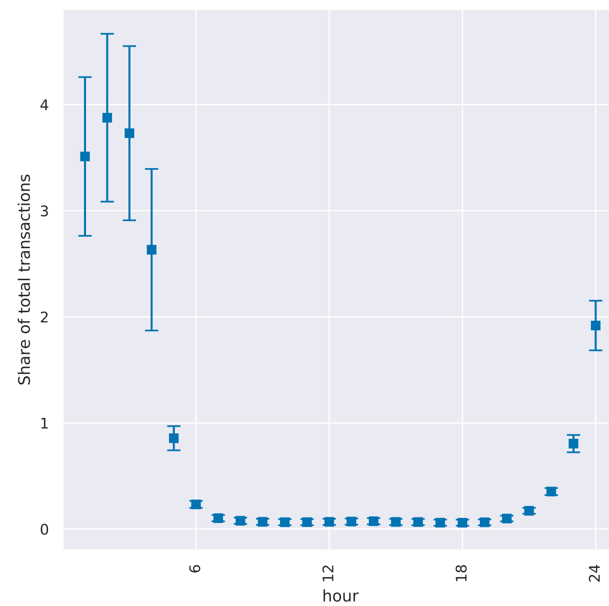
[47] This estimation requires that we have a dataset that indicates for each customer if a recharge transaction happened at any hour of the day. As the memory requirement grows exponentially, we use a random sample with a third of the original subscribers, and aggregate the transactions between midnight and 5am, and 10 and 11pm into a single dummy. After several iterations we do not find that the results change significantly if we draw a different random sample.

Figure 11: Share of amount borrowed per hour

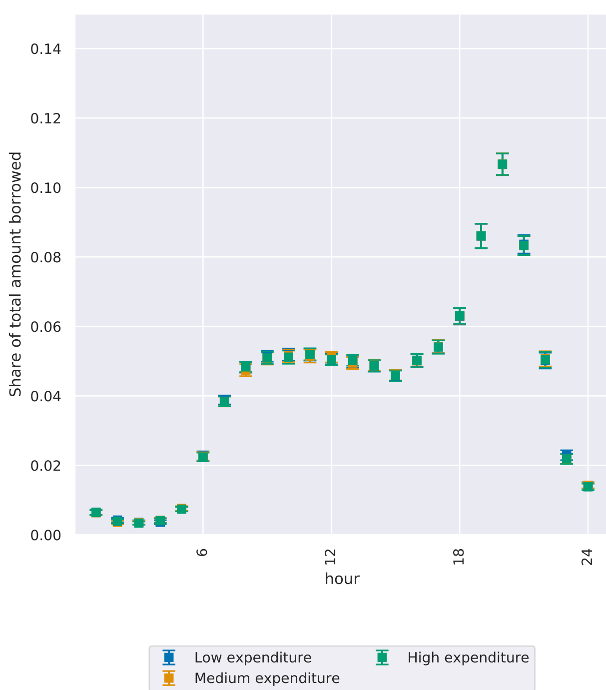
(a) Amount borrowed



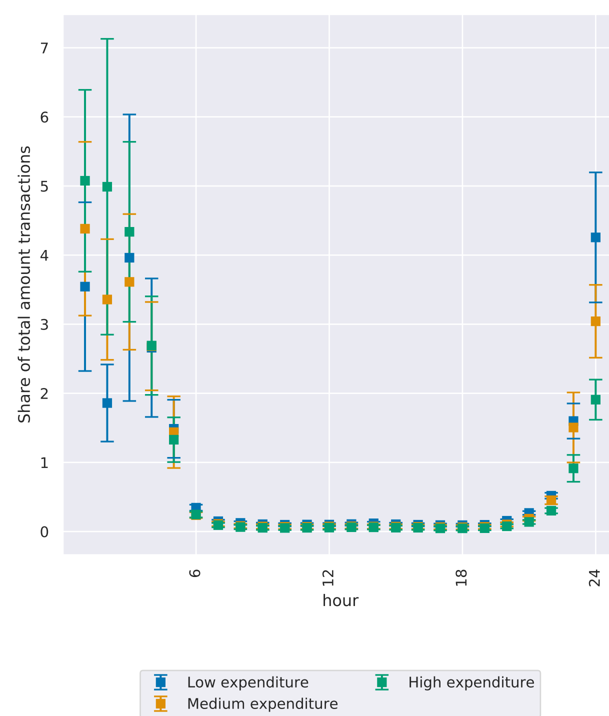
(b) Amount borrowed over amount recharged



(c) Amount borrowed
by initial expenditure tercile



(d) Loan transactions over recharges transactions
by initial expenditure tercile



Note: Includes only customers that are eligible for the loans. The estimation of daily demand patterns includes controls for day of the week and calendar week.

Figure 12: Changes in recharge probability

Note: Includes only long-term customers. Transactions before 6am were aggregated

7 Conclusions

There are several challenges to provide credit access to segments of the population that are not served by traditional formal financial institutions. Digital credit has the potential to reach these part of the market by solving the information asymmetries and bypass large transaction cost. We do not expect that a single product can serve all the diverse financial needs that exists in this segment of the market. Nevertheless, it is difficult to think that products that depend on physical locations can easily become attractive in areas where banking and other infrastructure is limited, and very expensive to develop.

We show that short-term financial constraints seem to have an impact in the consumption decision of low-income individuals. The widespread availability of airtime loans and the high demand that exists for the product show the potential for the introduction of new products. The level of risk and know-how of each new product determines how fast it can be introduced in the market. Airtime loans are leading the way to make MNO more comfortable with providing fully digital loans. Experience with airtime loans can make MNO to build the knowledge base necessary to launch new digital credit products to the market. Additionally, from the consumer perspective, airtime loans offer the possibility to gain experience with their first formal financial product.

Our findings show that low income populations are not able to adjust their communication consumption using the saving and informal credit methods available to them. A situation that makes their consumption decisions extremely sensitive to the timing of their income, and can potentially have negative welfare effects. This sensitivity can have serious ramifications in their capacity to manage negative shocks that extend beyond the realms of cellphone expenditure.

Several questions remain. First, we cannot provide a definite answer on the welfare effects of increasing cellphone expenditure. Fully answering this question would require to know the role cellphone communication plays in the income generating process, as well as its interactions with other credit sources. Evidence suggests that cellphone communication plays a role in the income generating process by providing information on market prices, and insurance through a long-distance risk sharing network that is key to manage covariate shocks (Jensen, 2007; Blumenstock *et al.*, 2016).

Second, more research is necessary to understand to what extend convenience and liquidity constrains contribute to the demand of digital credits, together with its implications on the welfare effects of increasing credit access. Easy access to credit can have positive affects for groups that are highly liquidity constrained, a results that seems confirmed by Bharadwaj *et al.* (2019), where the authors find that digital loans reduce vulnerability to shocks. However, the internal validity of their results makes that there is no evidence on how less vulnerable groups react to an increase in their credit limit. Our results suggests that loan demand in less vulnerable groups is driven by factors other than liquidity.

Third, airtime loans is a first step towards using MFS for financial inclusion. The small size of the loans is an advantage that allows for their introduction is most markets. However, as the market moves towards products with higher risk levels, more research must be placed to find the

the best way to leverage the experience of airtime loans, and on the optimal system of repayment incentives. Research shows that there is an optimal loan-size that encourages repayment, and that larger than optimal loans make customers more likely to default (Carlson, 2018).

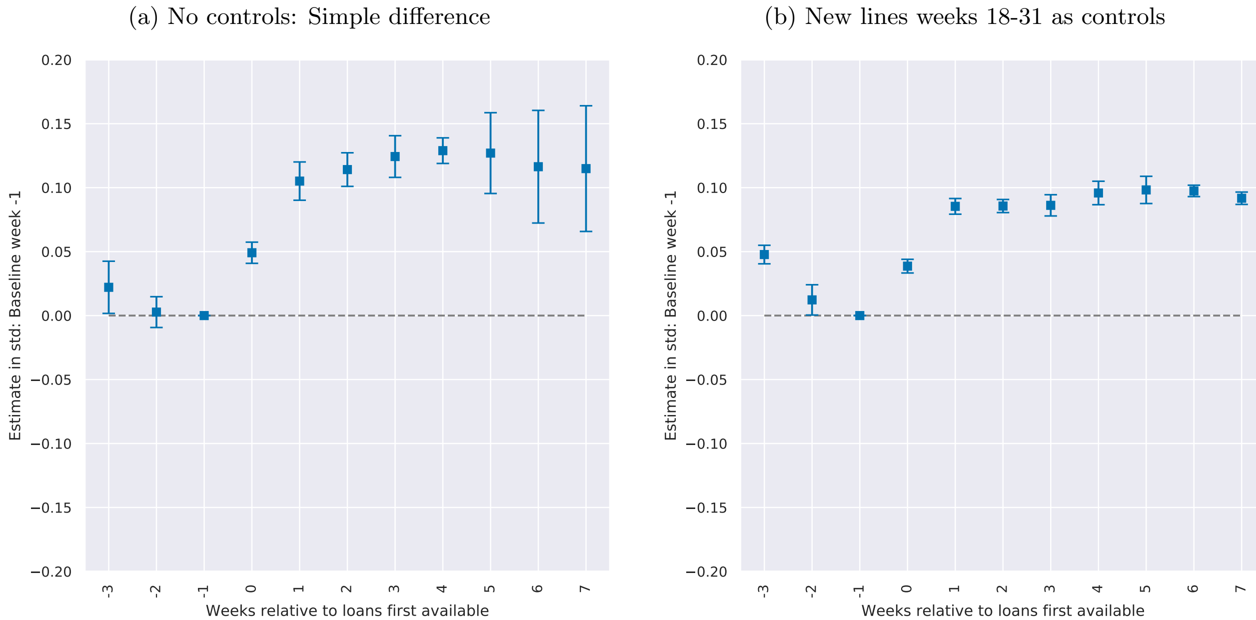
In summary, after adding 700 million new users in the past decade the cellphone market still has enough room to add new customers, with a vast potential to develop new products. Most of these new customers have low incomes, and completely skipped the ownership of a bank account and even a landline GSMA (2019). The experience of microfinance and payday lending offers a cautionary of the risks of providing credit to people that have binding liquidity constraints, high marginal returns to capital, and difficulty copying with unexpected shocks. Properly managing these risks depends on a constant investment on better credit scoring algorithms, and an environment that fosters competition between providers reducing fees. Above all, research on digital credit must continue in order to improve the methods to screen customers, better tailor consumer protection policies, and create better channels to guarantee that customers are fully informed of the costs of credit and their conditions.

8 Robustness exercises

8.1 Additional specification tests

We implement two additional specifications were we modify the control group that we use in our preferred specification. The first one implements a pure Event Study Design and does not include a control group, while the second one uses the new subscribers that joined the network during wees 18 to 24 of 2019 as the control group for those that joined latter. Figure 13 shows our results are robust to changes in the control group.

Figure 13: Event study
Additional specifications



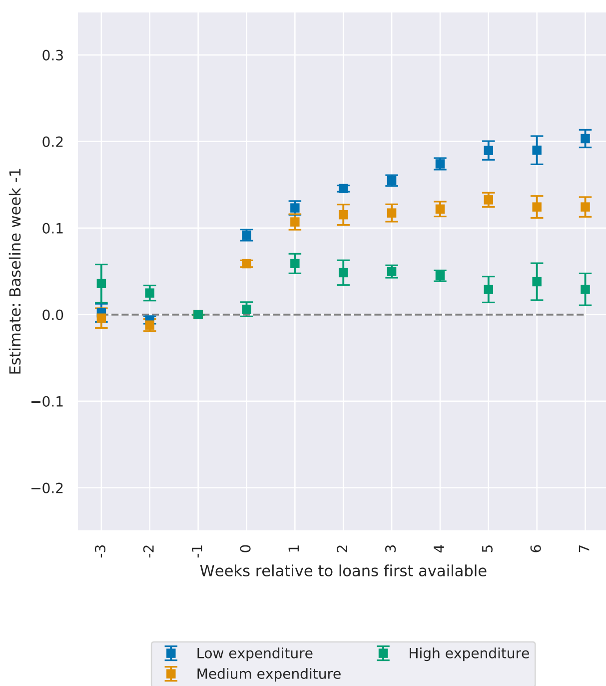
Note: Includes only customers that are eligible for the loans. Panel (a) uses only the sample that enter the network between the week 18 and 31 of 2019. Panel (b) uses as control the lines that were activated between week 18 and 24, and checks for the impact of airtime eligibility on lines activated between 25 and 31. During this period, the eligibility of lines activated between week 18 and 24 does not change.

8.2 Results by location of subscribers

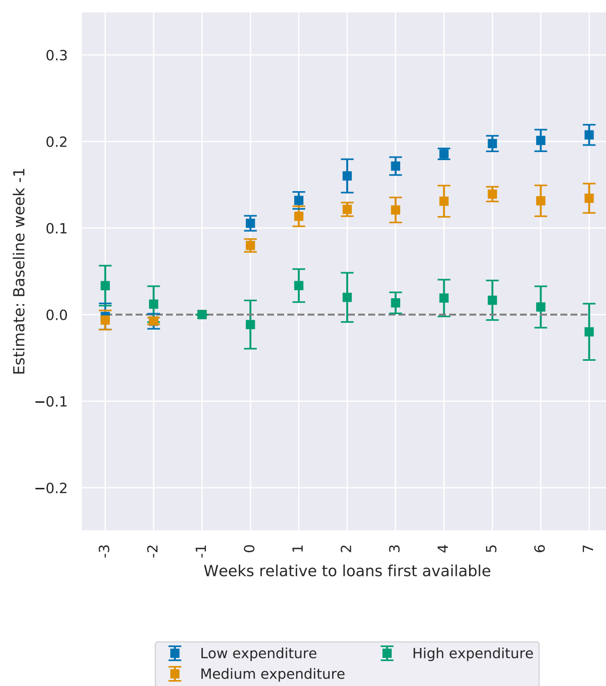
Descriptive analysis shows that expenditure levels differ depending on the location of subscribers, with new subscribers being more likely to be located outside of the Port-au-Prince metropolitan area. We test for differences in our parameter of interesting based on the location of subscribers. Overall, we find that credit access presents a similar affect across different locations.

Figure 14: Impacts credit access
Results by location of subscribers size

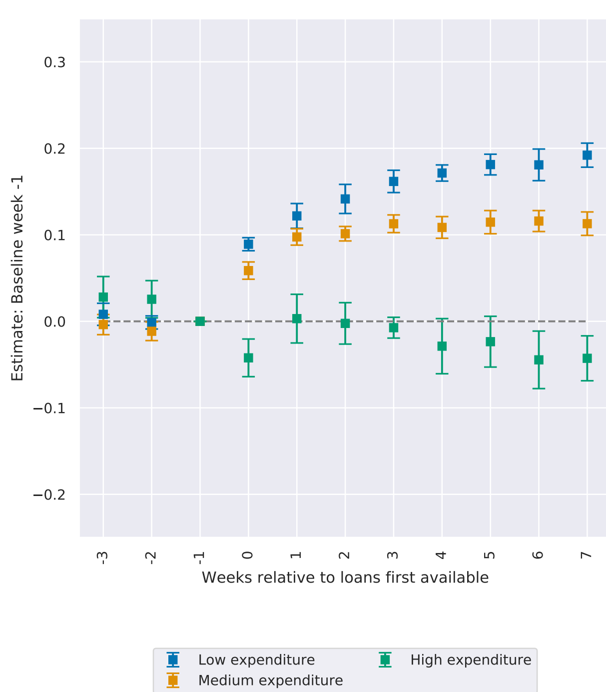
(a) PAP metropolitan area



(b) Large city



(c) Other



Note: Includes only customers that are eligible for the loans. Panel (a) uses only the sample that enter the network between the week 18 and 31 of 2019. Panel (b) uses as control the lines that were activated between week 18 and 24, and checks for the impact of airtime eligibility on lines activated between 25 and 31. During this period, the eligibility of lines activated between week 18 and 24 does not change.

Table 7: Impacts credit access
Results by city size

	Low expenditure			Medium expenditure			High expenditure		
	Baseline	Effect	Δ in percentage	Baseline	Effect	Δ in percentage	Baseline	Effect	Δ in percentage
Expenditure (USD)									
PAP metropolitan area	0.23	0.35***	156.06	0.64	0.26***	40.68	1.61	0.04***	2.44
Large cities	0.22	0.36***	160.11	0.64	0.26***	40.86	1.67	-0.01	-0.65
Other	0.21	0.29***	139.3	0.62	0.21***	33.66	1.62	-0.08***	-4.93
Avg. recharges (USD)									
PAP metropolitan area	0.14	0.07***	47.32	0.24	0.02***	9.88	0.44	-0.02***	-4.03
Large cities	0.13	0.08***	56.19	0.24	0.04***	15.33	0.49	-0.04***	-7.72
Other	0.14	0.07***	50.95	0.27	0.02***	8.15	0.52	-0.06***	-10.8
Number of recharges									
PAP metropolitan area	1.0	0.9***	89.36	2.59	0.31***	11.91	4.25	-0.23***	-5.49
Large cities	1.0	0.8***	80.4	2.58	0.18***	7.1	4.01	-0.23***	-5.69
Other	0.87	0.56***	64.8	2.23	0.07***	3.04	3.56	-0.35***	-9.91
Outgoing contacts									
PAP metropolitan area	4.65	1.32***	28.39	8.06	-0.46***	-5.68	9.66	-0.8***	-8.32
Large cities	4.02	1.26***	31.42	6.27	-0.06	-0.94	7.57	-0.38***	-5.08
Other	4.28	1.11***	26.02	6.44	-0.17***	-2.61	7.62	-0.41***	-5.44
Outgoing transactions									
PAP metropolitan area	17.6	15.77***	89.57	44.27	2.85***	6.43	69.85	-7.11***	-10.17
Large cities	16.81	14.66***	87.19	37.82	4.44***	11.75	56.03	-3.57***	-6.37
Other	17.36	13.03***	75.08	37.76	2.37***	6.28	53.95	-3.15***	-5.83
Avg. call duration									
PAP metropolitan area	62.53	2.54***	4.07	84.62	-7.08***	-8.37	96.78	-6.69***	-6.91
Large cities	52.78	3.42***	6.48	68.86	-5.48***	-7.95	78.79	-3.94***	-5
Other	54.47	2.18**	4	71.77	-5.46***	-7.61	83.48	-5.05***	-6.04
Gambling expenditure (USD)									
PAP metropolitan area	0.0	0.0***	132.39	0.01	0.0*	7.96	0.01	-0.0***	-11.89
Large cities	0.0	0.0***	53.56	0.01	-0.0	-7.68	0.01	-0.0	-8.37
Other	0.01	0.0***	22.79	0.01	-0.0*	-10.21	0.01	0.0	0.27

Note: PAP metropolitan area includes the city of Port-au-Prince and adjacent cities including Croix-de-Bouquets. Large cities group include the urban centers with more than 100,000 people. Each group concentrate 28 and 30% of all the Haitian population.

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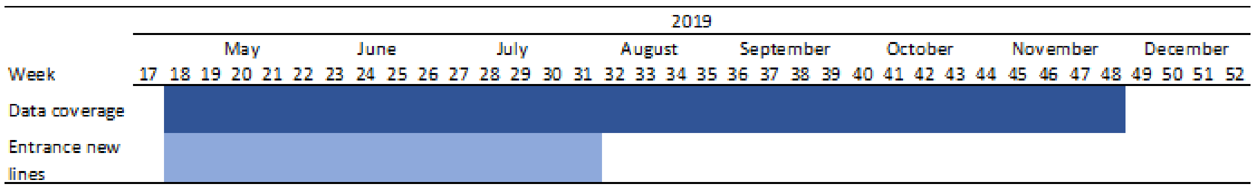
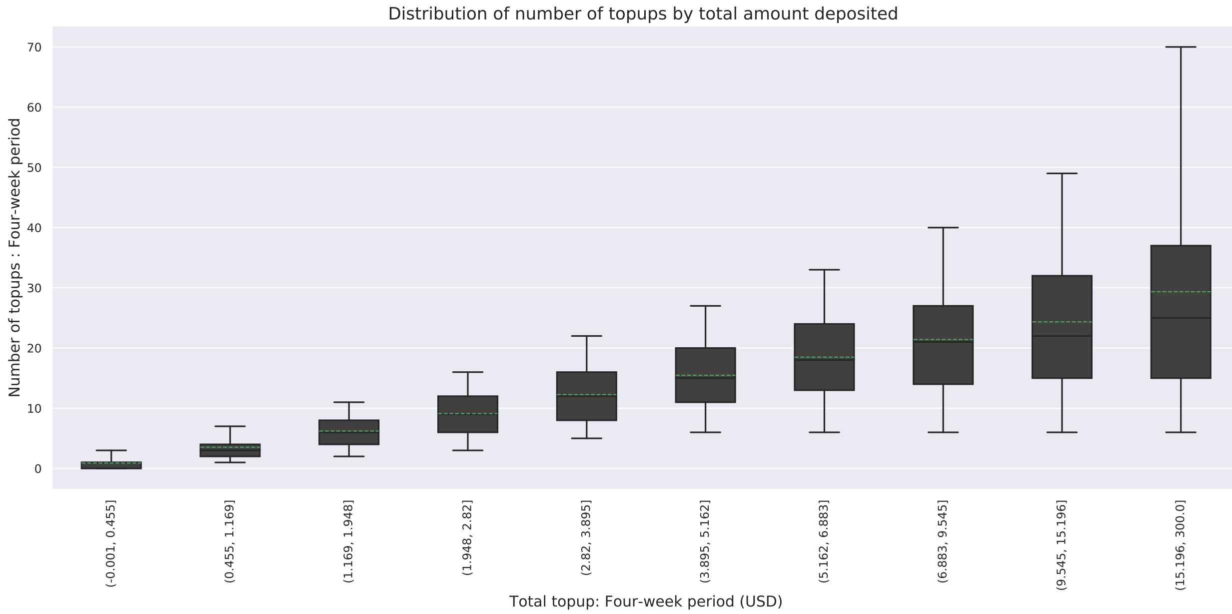
9 Appendix

Figure 1A: Cellphone data coverage



Note: Calendar-week includes Monday to Sunday and can overlap with the calendar month. Entrance new lines defines the period when we observe new lines being activated. The period after these weeks is used to observe the network patterns of the lines active, but do not include additional new lines into the analysis.

Figure 2A: Active numbers April 2019
Total monthly expenditure number of recharges



Note: Includes well-established lines only. The x-axis contains the deciles for total cellphone expenditure for April 2019.The y-axis contains the distribution of 95% of number of recharges for each subscriber during the month. Vertical lines show the minimum and maximum values.

Figure 3A: Time in the network
New numbers May and July 2019

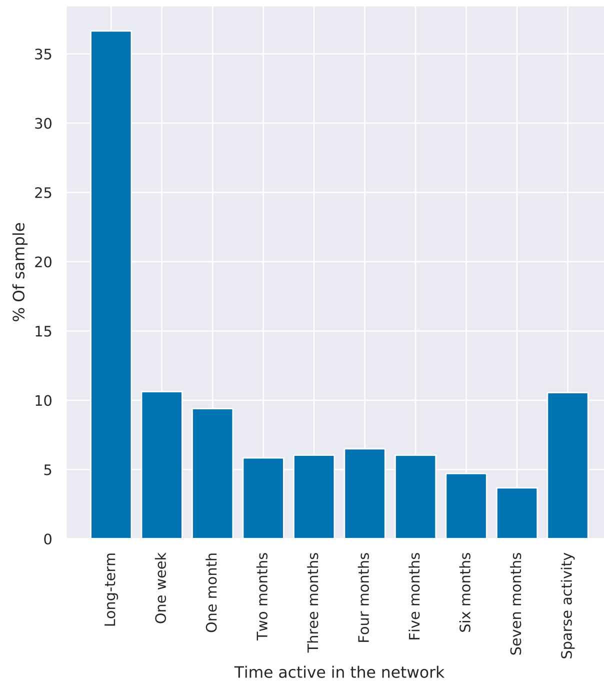


Figure 4A: Percentage of each group using airtime loans each week

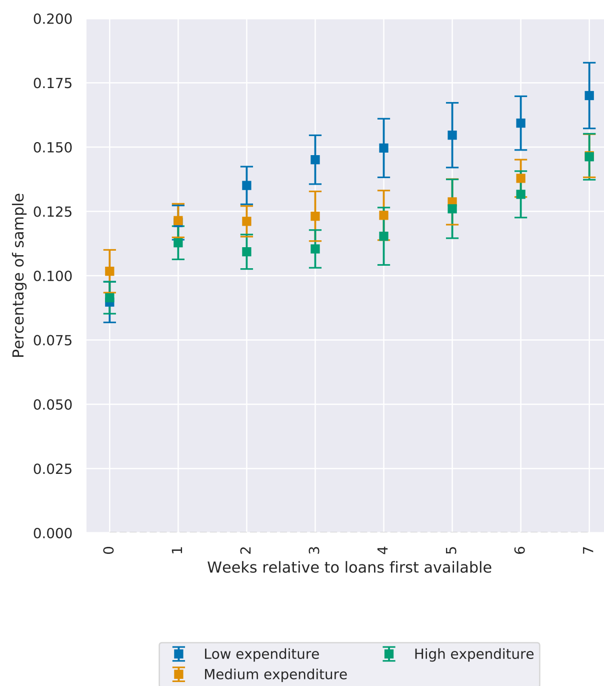
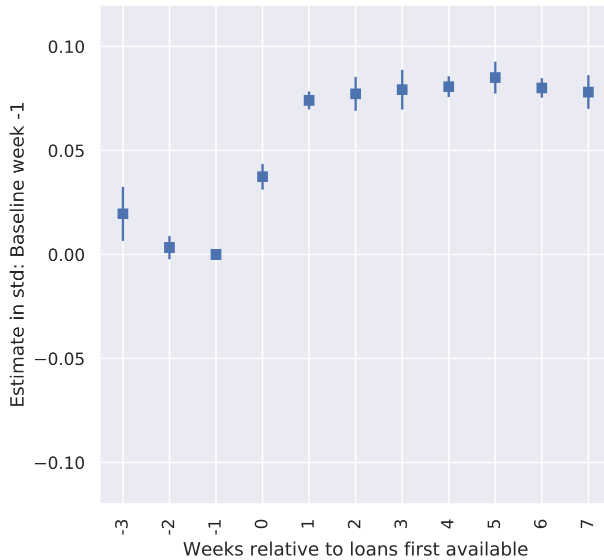
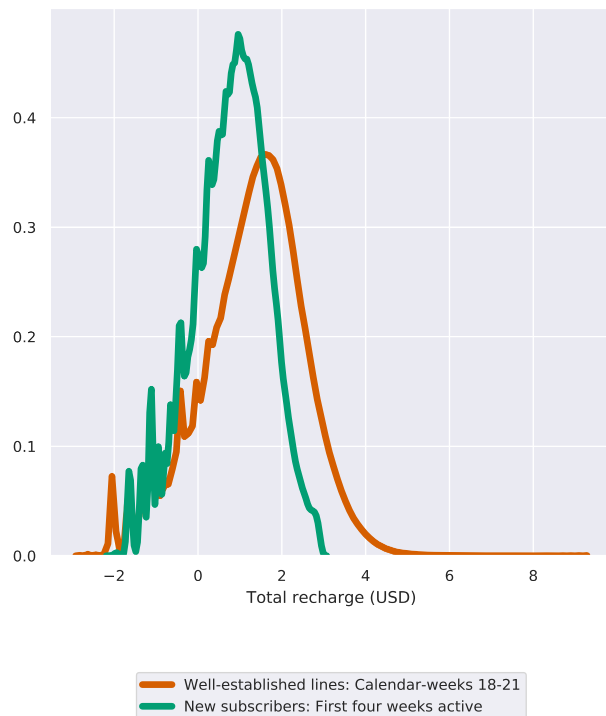


Figure 5A: All new customers more than 3 month active
Total weekly expenditure



Note: Includes only long-term and customers that were active for more than three months. Loan access is provided at week 0 and the week before is used as baseline.

Figure 6A: PDF cumulative expenditure



Note: Includes only long-term customers. Loan access is provided at week 0 and the week before is used as baseline.

Table 1A: Distribution of population and active cellphone subscribers

Department	**Population**	**Percentage of population**	**Well established lines**	**New customers**
Artibonite	1,727,524	15.8%	7.1%	9.0%
Centre	746,236	6.8%	2.2%	3.5%
Nord-Ouest	728,807	6.7%	2.1%	2.9%
Nord	1,067,177	9.8%	8.1%	8.3%
Nord-Est	393,967	3.6%	1.0%	1.7%
Grand'Anse	468,301	4.3%	1.0%	0.8%
Nippes	342,525	3.1%	2.6%	2.8%
Sud	774,976	7.1%	4.3%	4.2%
Ouest	4,029,705	36.9%	65.9%	60.4%
Sud-Est	632,601	5.8%	5.6%	6.5%

Note: Population information comes the 2018 National Population Projection

Table 2A: Descriptive statistics
Phone survey

	mean	std	min	10%	50%	90%	max
Demographics							
Age	31.59	9.13	16.0	22.0	30.0	43.0	87.0
Household Head	0.62	0.49					
Gender	0.55	0.5					
Labor Market							
Worked last week	0.41	0.49					
Income regular week (USD)	83.61	115.73	2.14	14.29	50.0	171.43	1071.43
Income last week (USD)	78.35	103.13	0.0	14.29	50.0	142.86	814.29
Income stability							
Unpredictable	0.58						
Somewhat unpredictable	0.28						
Very predictable	0.14						
Food security							
Small serving	0.64	0.48					
Borrowing							
Neighbor	0.27	0.44					
Amount (USD)	258.22	385.47	2.86	21.43	142.86	714.29	2857.14
Family	0.2	0.4					
Amount (USD)	413.29	1359.55	7.86	37.21	142.86	671.43	10742.86
Bank	0.07	0.25					
Amount (USD)	9824.17	48403.56	35.71	264.29	1428.57	4714.29	300000.0
Shopkeeper	0.04	0.2					
Amount (USD)	100.23	158.23	7.14	13.14	26.79	407.14	500.0
Informal	0.02	0.14					
nan	235.58	159.28	21.43	28.57	214.29	398.57	500.0

Note: Includes 589 survey participants with matched cellphone records.

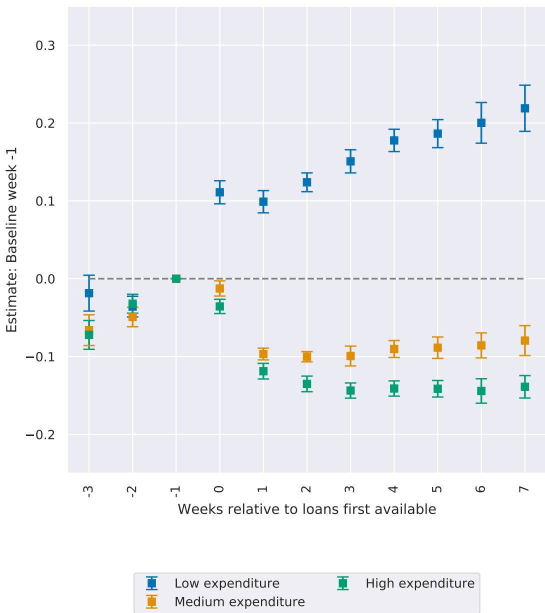
Table 3A: Network transactions statistics
Four weeks prior to survey

	mean	std	10%	50%	90%
Recharge Activity					
total recharge (USD)					
Very predictable	36.84	73.42	5.7	19.48	53.58
Somewhat unpredictable	21.88	20.77	5.09	15.26	46.12
Unpredictable	20.99	26.86	4.76	12.9	42.34
Number of recharges					
Very predictable	28.85	15.02	13.0	27.0	50.8
Somewhat unpredictable	27.88	16.54	11.0	23.5	52.3
Unpredictable	28.11	15.34	12.0	24.0	50.0
Average recharge					
Very predictable	85.88	112.82	18.67	53.75	162.69
Somewhat unpredictable	59.84	48.86	18.0	42.15	112.29
Unpredictable	57.75	81.97	15.4	36.63	108.44
Median recharge					
Very predictable	62.44	99.83	14.39	45.45	100.0
Somewhat unpredictable	47.63	46.1	14.25	25.0	95.46
Unpredictable	39.02	44.26	12.83	25.0	84.91
Number of loans					
Loan Demand					
Very predictable	3.76	3.1	1.0	3.0	8.9
Somewhat unpredictable	3.66	2.9	1.0	3.0	8.0
Unpredictable	3.44	3.41	1.0	2.0	7.0
Total amount borrowed (USD)					
Very predictable	5.29	6.78	0.39	3.1	10.61
Somewhat unpredictable	4.76	5.32	0.39	2.91	9.6
Unpredictable	4.3	5.81	0.27	2.59	11.6
Share of total expenditure financed					
Very predictable	0.21	0.17	0.02	0.19	0.44
Somewhat unpredictable	0.26	0.22	0.03	0.2	0.57
Unpredictable	0.21	0.17	0.02	0.18	0.45

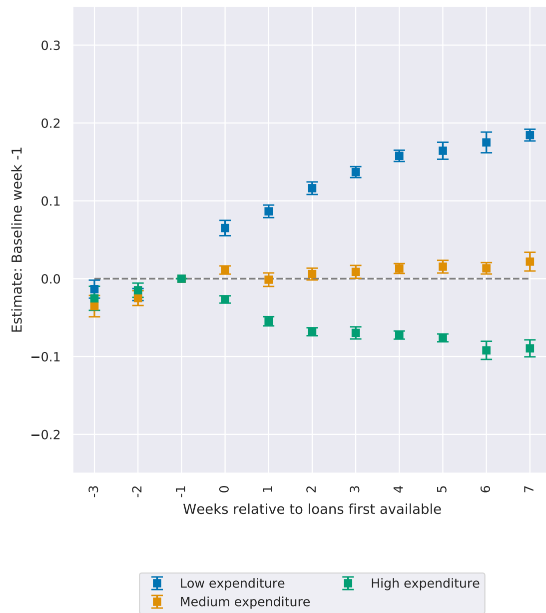
Note: Includes 589 phone survey participants that match cellphone records. Descriptive statistics on cellphone data include one month of mobile transactions.

Figure 7A: Heterogeneous impacts
Key network metric activities

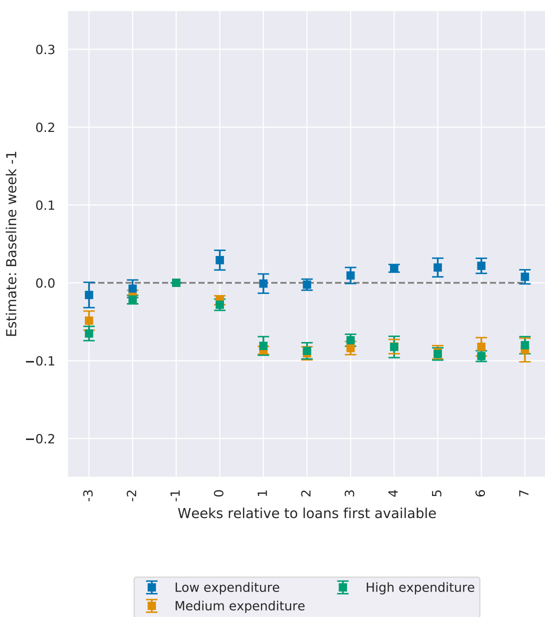
(a) Total number of contacts per week



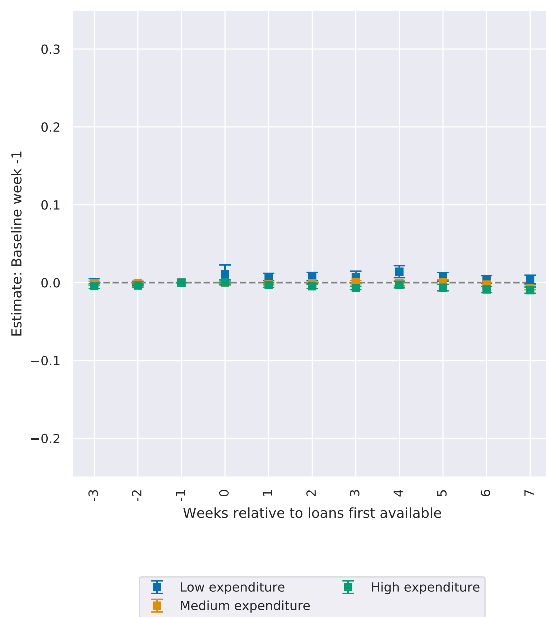
(b) Total outgoing transactions per week (calls+SMS)



(c) Average duration of calls



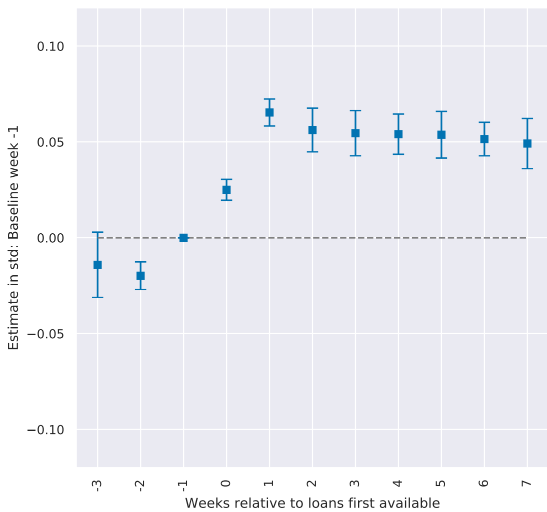
(d) Total expenditure in gambling



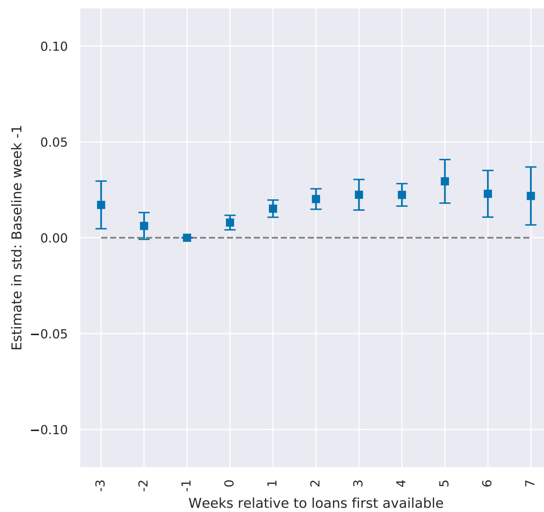
Note: Includes only long-term customers. Results are in standard deviations and use week -1 as baseline.

Figure 8A: Additional results on recharges: Frequency and and amount

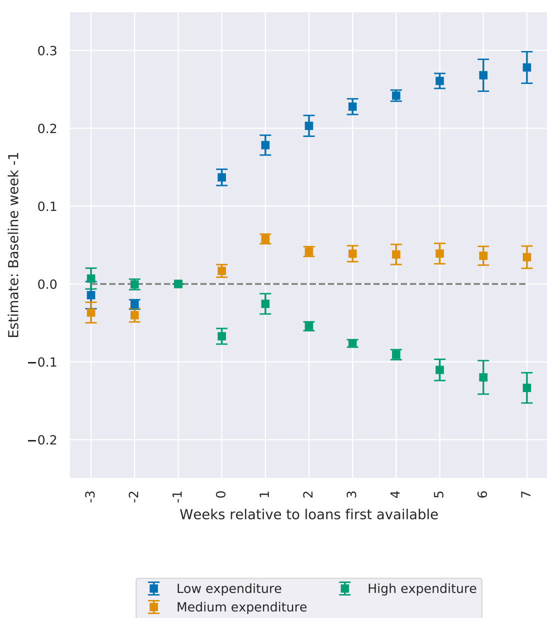
(a) Number of recharge transactions



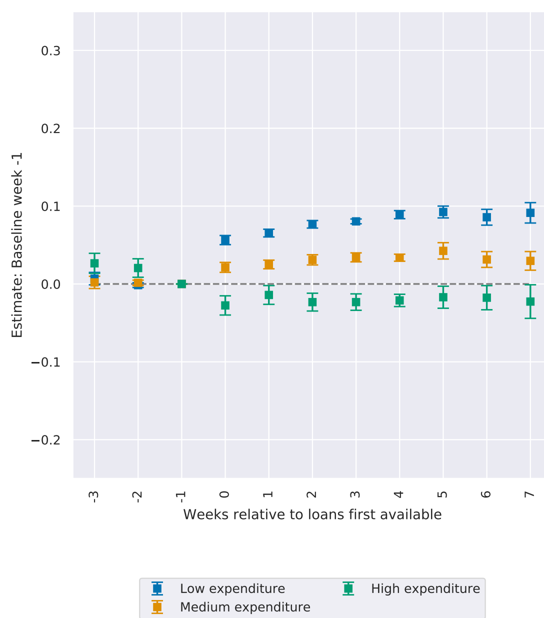
(b) Average recharge amount



(c) Number of recharge transactions: By group

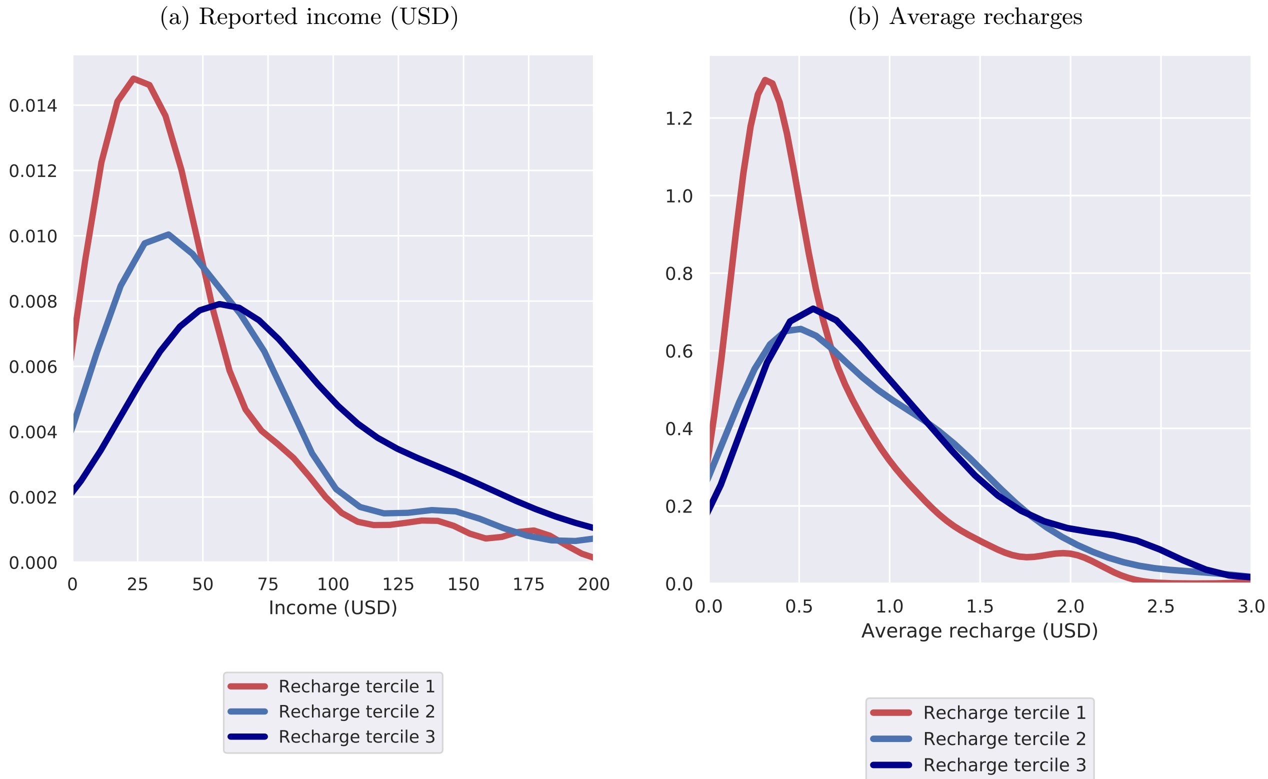


(d) Average recharge amountBy group



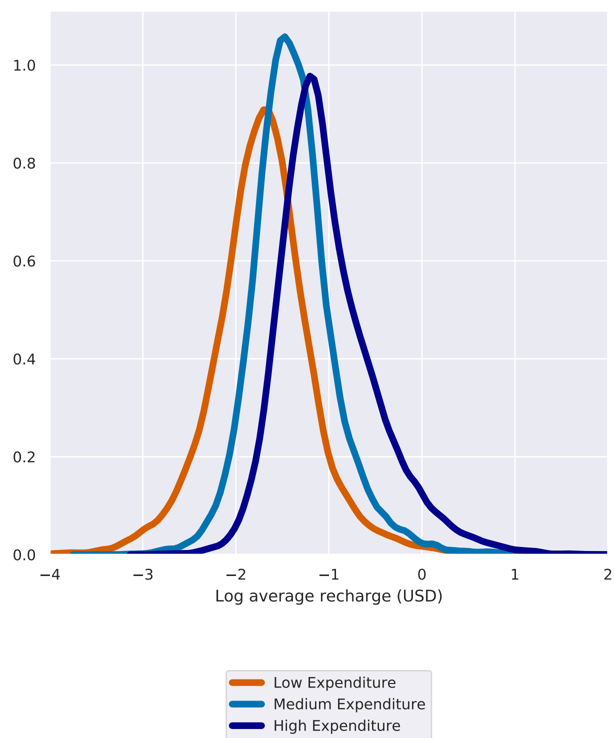
Note: Includes only long-term customers. Results are in standard deviations and use week -1 as baseline.

Figure 9A: Recharge terciles and observed income
phone survey participants only



Note: Recharge terciles were constructed using the distribution of total cellphone expenditure in the month before the survey. Information on the reported income during the previous week is only available for those that were employed at the time of the survey.

Figure 10A: Average transaction size (USD)
Long-term customers



Note: Average transaction size during the initial 4 weeks

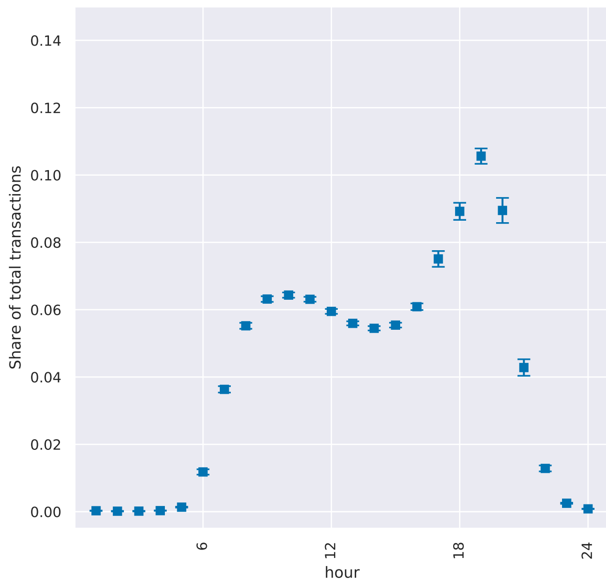
Table 4A: Share of total expenditure finances by principal and facilitation fee

Week active	Principal						Facilitation fee					
	Low		Medium		High		Low		Medium		High	
5	5.71	(0.78)	5.25	(0.69)	4.5	(0.39)	0.69	(0.09)	0.57	(0.07)	0.43	(0.04)
6	8.69	(1.68)	7.45	(0.81)	6.29	(0.54)	0.98	(0.17)	0.76	(0.08)	0.6	(0.05)
7	10.6	(2.33)	8.57	(1.26)	6.79	(0.66)	1.14	(0.23)	0.85	(0.12)	0.64	(0.07)
8	12.2	(3.08)	9.44	(1.86)	7.29	(0.86)	1.26	(0.29)	0.92	(0.18)	0.69	(0.08)
9	13.37	(2.86)	9.86	(1.61)	7.97	(1.0)	1.35	(0.27)	0.95	(0.16)	0.75	(0.1)
10	13.93	(2.99)	10.17	(1.55)	8.49	(1.25)	1.4	(0.29)	0.99	(0.15)	0.8	(0.12)
11	15.13	(3.0)	10.94	(1.49)	8.45	(0.81)	1.5	(0.28)	1.06	(0.14)	0.8	(0.08)
12	16.12	(2.52)	11.82	(1.54)	9.34	(1.04)	1.59	(0.24)	1.14	(0.15)	0.88	(0.1)

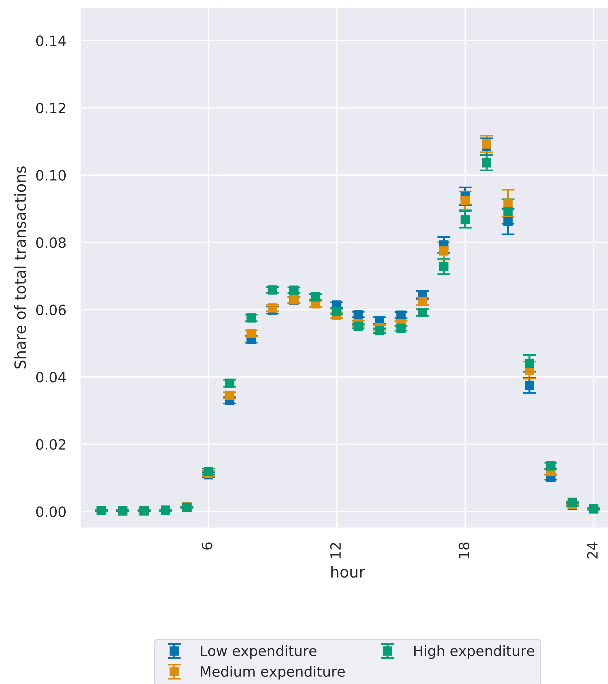
Note: Long-terms customers only. Groups defined using total cellphone expenditure before loans are available

Figure 11A: Share of total recharge per hour
Long-term customers

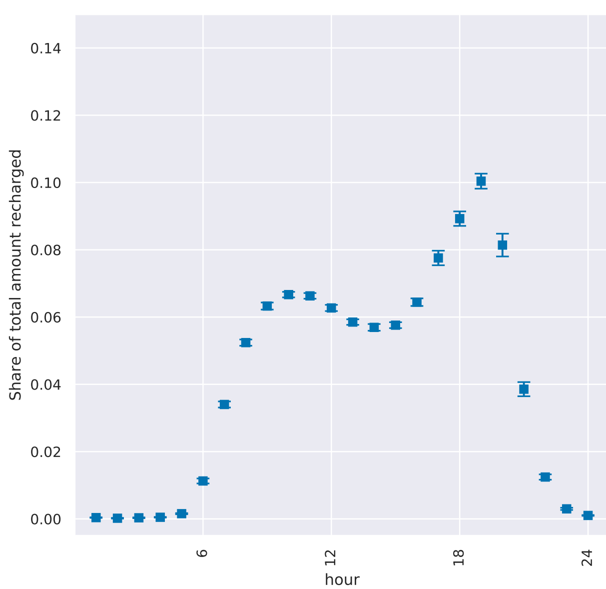
(a) Total number of recharges



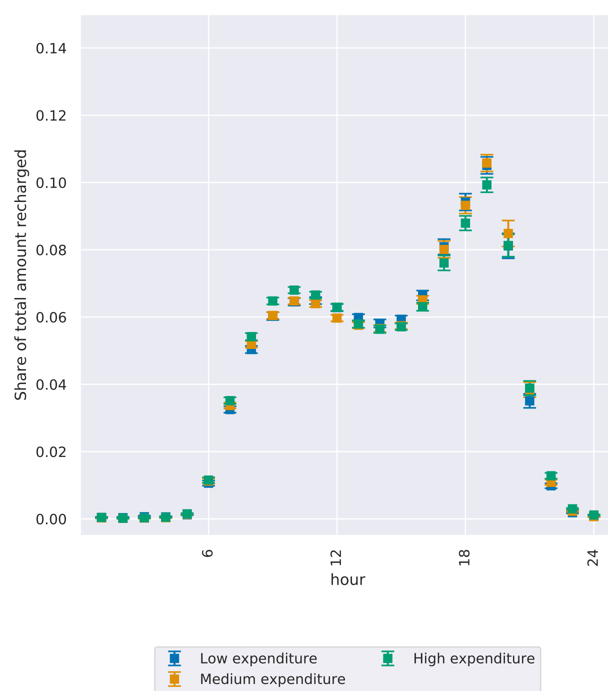
(b) Total number of recharges: Initial tercile expenditure



(c) Total amount recharged



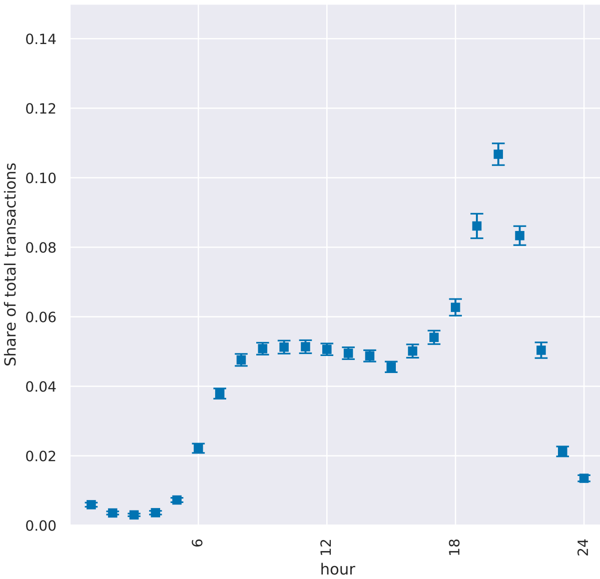
(d) Total amount recharged: Initial tercile expenditure



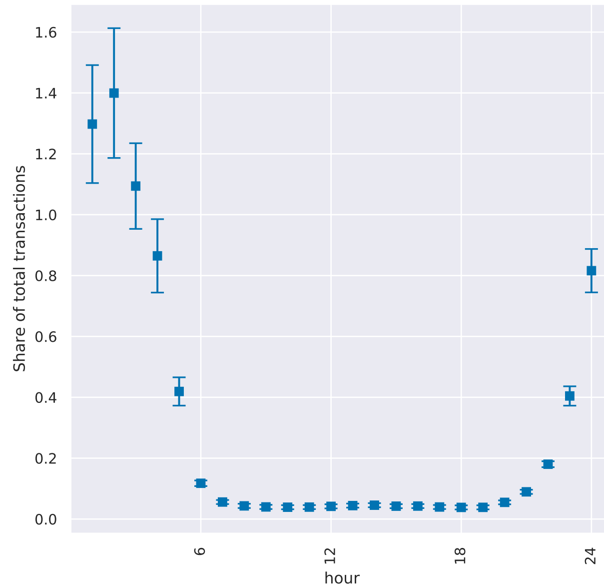
Note: Includes only customers that are eligible for the loan. The estimation of daily demand patterns includes controls for day of the week and calendar week.

Figure 12A: Share of loan transactions per hour

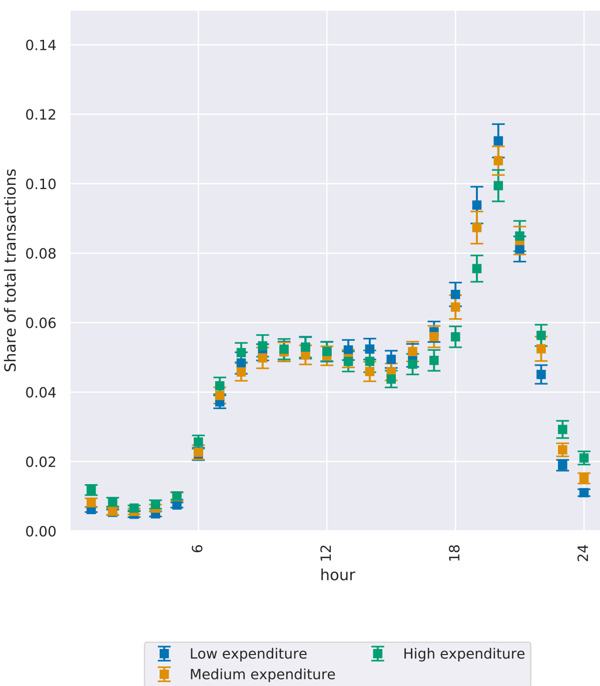
(a) Loan transactions



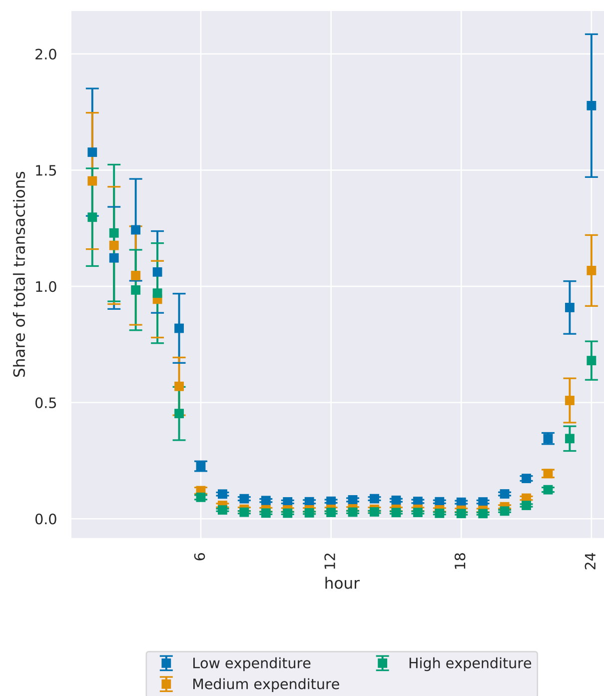
(b) Loan transactions over recharges transactions



(c) Loan transactions
by initial expenditure tercile



(d) Loan transactions over recharges transactions
by initial expenditure tercile



Note: Includes only customers that are eligible for the loans. The estimation of daily demand patterns includes controls for day of the week and calendar week.