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*

October 7, 2020

Abstract

Credit market imperfections make households more vulnerable to shocks and their consumption decisions extremely sensitive the timing of their income. Algorithmic insights from individual meta data have enabled a proliferation of mobile financial services to cellphone users 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 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) has 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 liquidity becomes a non-trivial, often 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. It consists in a very simple product that 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 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,

[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.

but it seems clear that these costs 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 several mechanisms through which airtime loans can cause an increase in expenditure. These include the existence of a binding liquidity constraint the forces customer to reduce their cellphone activity when they lack funds to pay for calls, a reduction on the salience of the costs of calls as customer can avoid visiting vendors and paying with cash, and the existence of 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

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

often survive day-to-day on razor thin cash balances 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 that 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 these loans primarily for the convenience they offer as it allows them to reduce the frequency they need to look for a vendor to recharge, and to strategically move the timing of their transactions to times they find more convenient. In our setting, the loan facilitation fee of 10% provides an upper bound for the transaction costs this customers perceive recharging at inconvenient times have. 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) finds 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 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 showing its potential to alleviate credit market failures. The study of airtime loans has been overlooked, with more attention been placed on products that provide larger uncollaterallized loans that can be converted into cash. However, these products have seen a slower adoption rate as they have higher risk levels, and demand a larger investment from the MNO in terms of know-how and product deployment. This lower adoption rate limits the evidence available about the impacts of these products, with only one study available.[5] Bharadwaj *et al.* (2019) studies the first digital credit product launched in Kenya in 2012. Loans are on average, ten times larger that the average airtime loan.[6] Interestingly, an important percentage is still used to cover airtime. Similar 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

[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

as they show digital credit increases the resilience of households to shocks.[7]

Second, we contribute to the understanding of how demand for digital loans responds both to liquidity needs and the additional convenience that easy access to credit provides. We show that despite relatively uniform patterns of loan usage between poor and non-poor subscribers, a convenience effect dominates in customers with high income, while demand from lower income subscribers is driven by the need of liquidity. This result is important because it raises concerns on how digital credit can affect better-off consumers, for who the convenience of easy access to cash can create overindebetdness problems. Two ideas complment this resutls. First, there is already evidence that the expedience of fund delivery has a detrimental effect on the repayment probability (Bulando *et al.*, 2020). Second, the results that show positive impacts of digital credit rely on regression discontinuity designs, which makes them internally valid only in a small window around the credit score cut-off. People inside that window tend to have higher levels of poverty and vulnerability than the rest of the population. However, current evidence is not sufficient to know digital credit affects people with lower levels of vulnerability, who might find easy access to capital tempting, but with negative impacts. Even if not totally comparable, the evidence from the payday loans industry in the US seems to indicate that consumer credit has 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).

Our last contribution is on the way 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

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

(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 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 in context

Since the early 2012, more than 50 billion dollars have been invested in developing the financial technologies sector with the objective to create new products that appeal to a much broader set of borrowers (McKinsey, 2017). Financial technologies (FinTech) includes all the services that improve and automate the delivery of financial services. The lines that differentiate products are usually blurry since the same company can provide the same product through different platforms. 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. First, it manages information asymmetries using non-traditional data sources that allow it to provide individualized credit scores without the need of 'hard' data, such as proof of income, employment or a formal credit histories. Second, it has lower costs to provide services as it relies in the infrastructure of cellphone companies. Third, and building in the previous two points, digital credit can dramatically lower transaction costs by

[8] Also called mobile credit and digital lending

eliminating wait-time periods other costs associated with applying on physical locations.[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. Depending on how taxing these constrains are, there are three tiers of services.

The first tier involves the lowest level of risk exposure for providers, and is where airtime loans are located. In products in this category the MNO leverages the cellphone's data 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. Defaulting a loan has the consequence 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 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 airtime loan products 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 that rely on bank accounts to disburse funds. These products are provided by traditional lenders that

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

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 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 of digital credit contains products with two main characteristics. First, the lender lacks 'hard' data, such as proof of income, employment or a formal credit history fully relying on other sources of data, usually cellphone metadata, to screen customers. Second, funds can be accessed, (and spent), using mobile money. The first product of this kind was launched in Kenyan in 2012, and during the first two years of existence it made over 20 million loans, many for sums of a few dollars, to 2.6 million borrowers (Cook and McKay, 2015).[11] 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 also be larger 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.[12] Yet, as airtime loans prove the feasibility of providing 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.

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

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

[12]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.

2.2 Cellphone customers 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).[13] 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 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.[14] As is the norm of the cellphone market in developing countries, the majority of cellphone customers are prepaid.[15] Postpaid plans are available but there are several reasons that hinder their adoption. First, they are expensive with the more affordable 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.[16]

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 per month in eleven different recharges. Individual recharges are small, with an average amount of only USD$0.30. Most customers are active everyday, and have, on average, 8

[13] 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)

[14] 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.

[15] 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.

[16] 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.

unique contacts in a regular week. This level of usage is similar to the ones found in other studies in the developing world, see Khan and Blumenstock (2016).[17]

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	0	1	4	11
Share of expenses financed	0.3	0.2	0	0	0	0	1

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: Access and demand

In Haiti, only prepaid customers have access to the product. The only eligibility restriction is that a phone number must have been in the network for thirty days, 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 qualifying. 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

[17] An entry level postpaid plan costs around 25 USD, Figure 4 shows how this more than the monthly expenditures of 95% of active customers. Figure 1A shows that there is a strong preference for small and frequent recharges that takes place along the whole distribution of total expenditure.

high demand for airtime loans is intrinsically linked to high dependence on prepaid plans. When a customer runs out of balance, he cannot initiate transactions unless they add balance to their accounts. Finding places to recharge is not difficult, with the option of using street vendors, formal shops, and mobile money. On a typical day 89% of all recharges are made with street vendors and 8% and using mobile money.[18]

Loans can be requested directly from any handheld device.[19] 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 provider the loan principal and a 10% facilitation fee before thirty days. 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.[20] 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.[21]

The only collateral for the loan is the customers' phone number. Preliminary qualitative work that inspired this document revealed that people have a very salient notion of the potential switching costs that a new number brings. These costs increase the longer a person has own the number and if the number is used in income generating activities. Most loans are fully repaid in less than 5

[18]Recharging using a mobile money account requires to have a positive balance and, currently, it is not possible to negative credit in the mobile money account.

[19]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 standard phones, feature phones and smartphones without the need to install any app, or the need of mobile data.

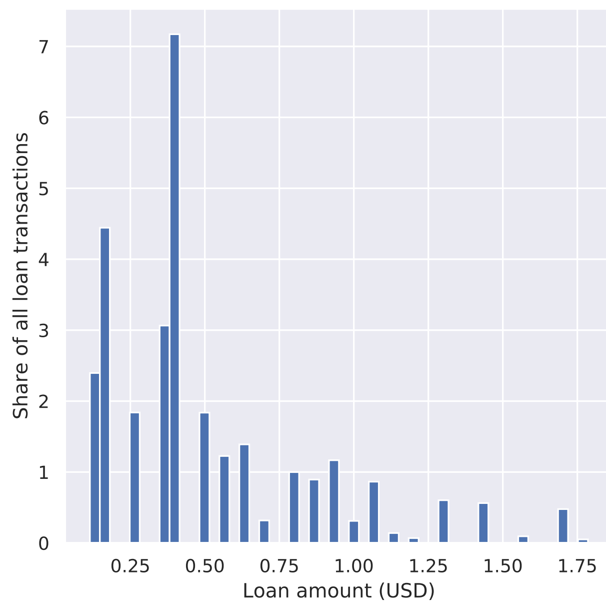
[20]One exception is balance transferred from another customer. In the case that balance transferred is less than the principal plus the origination fee, the customer receives 80% of the amount sent, and the rest is used to pay the loan.

[21]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

days with a very low default rate; a result that seems to validate the high valuation people place on their numbers that we found in the qualitative work.

Revealing the popularity of airtime loans, Figure 2(a) shows that as soon as the airtime loans become 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 1: Distribution of the amount of all loan transactions
May and November 2019

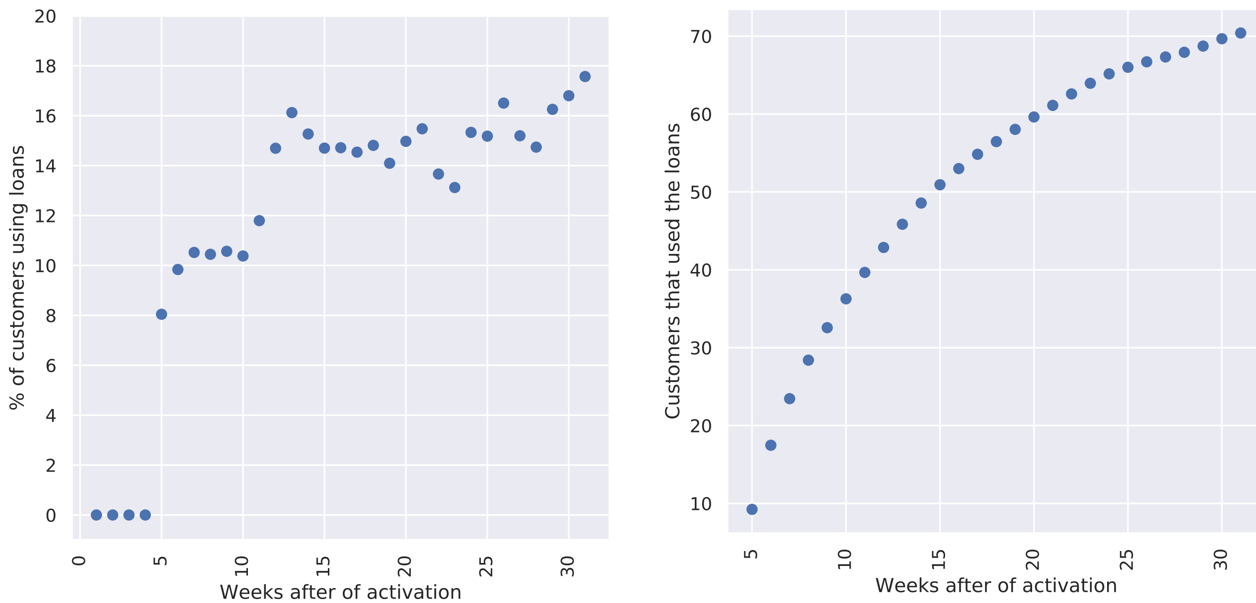


Note: Loan amounts are discrete values

Figure 2: Loan demand by week

(a) Percentage requesting loan

(b) Cumulative usage



Note: Includes only customers active more than 7 months in the network

3 Theoretical Model

We develop a microeconomic model of cellphone expenditure. There are several features that we want to highlight in a simple two-period model:

1. Airtime is a stock. Two characteristics differentiate it from cash. First, it can only be spent in cellphone consumption. Second, cash can be converted into airtime balance but not the other way around.

2. Airtime can be bought during any period. Every time the agent transform cash into balance, the transaction incurs a cost that we model as 'effort' ($\bar{e}$). We include effort to reflect that in order to recharge a customers must find a vendor first; a task that can be easy or hard depending on the time and location of the agent. Effort has always a negative impact on utility. However, it only affects income negatively if it is made during the first period. This

assumption reflects that the agent had to stop working to find the agent, but that recharging during non-working hours only affects utility by reducing leisure.

3. To reflect missing credit markets, the agent can only move income and airtime balance to the next period but not the other way around.

4. In the second period, the agent receives an additional payment that depend negatively on the amount of effort he used to search for airtime in the first period.

5. Cellphone consumption happens in both periods, subject to the stock of airtime.

6. Consumption of other goods takes place in the last period. There is a minimum consumption level that the agent must achieve that reflects a minimum calorie intake

Model setup

There are two periods. At $t = 1$, that we can think about as the beginning of the day, the agent starts with an amount of money equal to M, and a stock of airtime equal to zero ($B_1 = 0$). Both M and B can be transfer without loss, but the agent receives no return (or loss) in the process. During the second period ($t = 2$), that we can think about as the end of the day, the agent receives the salary for the day. The amount received depends negatively on the amount of effort he puts into looking for an airtime vendor.$S(1 - e_1)$.

Decision process:

Period 1

The utility of the agent during this period is given by: $u_1(m_1, e_1)$. Where m_1 represents the total number of minutes and agent talks during the period. If the agent buys airtime during the period, it must spend an amount of effort of at least $\bar{e}$. The size of $\bar{e}$ reflects how difficult it is to find an agent at the time. This means that he can only buy airtime if $e_1 \geq \bar{e}$. If he spends all of his time looking for a vendor we have: $e_1 = 1$.

$$u_1(m_1, e_1) = \begin{cases} u_1(m_1, e_1) \text{ if looks for airtime vendor} \\ \mathrm{u}_1(m_1, 0) \text{ if does not look for airtime vendor} \end{cases}$$

with $u_1(\bar{m_1}, e_1) < u_1(\bar{m_1}, 0)$ $\forall \bar{m_1} \geq 0$, $\frac{\partial u_1}{\partial m_1} > 0$, $\frac{\partial^2 u_1}{\partial m_1^2} < 0$ and $\frac{\partial u_1}{\partial e_1} < 0$

Calls are only possible when the stock of airtime is positive. The price of airtime equals P_b. The total cost of airtime is thus $b_i \times \mathrm{P}_m$, with b_1 being the total amount of airtime the agent buys in period one. For simplicity, we assume that the decision to buy airtime and calling happens simultaneously. The maximum amount of balance the agent can afford in this period is $P_m b_1 \leq M$, and in turn b_1 limits the consumption of minutes.

The agent chooses the optimal amount of minutes to consume at $t = 1$, and the remainder of the airtime balance, M, is transferred to the next period.

Period 2

At the start of the second period, the agent receives salary $S(1 - e_1)$. It depends negatively on the level of effort he put on buying airtime in the previous period. Therefore, the total amount of money available equals: $S(1 - e_1) + (M - P_m b_1)$

In this period, the agent has the option to increase the amount of airtime balance from its initial level of $b_1 - m_1$. To do this, the agent still needs to make an effort of at least $e_2 \geq \bar{e}$. As this is the end of the day, when we assume the agent is not working, effort has no negative impact on income. c_2 represents the consumption of other goods different than minutes. We assume that agent must consume a subsistence level of $c_2 > \gamma$

The utility during the period is given by:

$$U_2(m_2, e_2, c_2) = \begin{cases} v(c_2)u_2(m_2, e_2) \text{ if looks for airtime vendor} \\ \\ v(c_2)u_2(m_2, 0) \text{ if does not look for airtime vendor} \end{cases}$$

$U_2(\bar{m_2}, e_2, \bar{c_2}) < U_2(\bar{m_2}, 0, \bar{c_2})$ $\forall \bar{m_2}, \bar{c_2} \geq 0$, $\frac{\partial U_2}{\partial m_2} > 0$, $\frac{\partial^2 U_2}{\partial m_2^2} < 0$, $\frac{\partial U_2}{\partial c_2} > 0$, ,$\frac{\partial^2 U_2}{\partial c_2^2} < 0$ and $\frac{\partial u_1}{\partial e_2} < 0$

3.1 Maximization process in the absence of airtime loans

We assume functional forms for the agent's utility and income function $S(e_1)$. The utility maximization problem is the agent face is described by the following equations:

$$\underset{m_1,e_1,b_1,m_2,e_2,b_2,c_2}{max} \; {m_1}^{\alpha_1}(1-e_1)^{\alpha_2} + \beta\,[{m_2}^{\alpha_1}(1-e_2)^{\alpha_2}(c_2-\gamma)^{\alpha_3}](1) \text{ s.t.}$$

$$(2) \qquad m_1 \leq b_1$$

$$(3) \qquad P_b b_1 \leq M$$

$$(4) \qquad e_1 \leq 1$$

$$(5) \qquad m_2 \leq (b_1 - m_1) + b_2$$

$$(6) \qquad P_b b_2 + P_c c_2 \leq (M - P_b b_1) + S(e_1)$$

$$(7) \qquad e_2 \leq 1$$

$$m_1, b_1, e_1, m_2, b_2, e_2 \geq 0$$

In the absence of credit markets, two effects appear. First, an agent with a low level of M is constrained in their consumption of cellphone minutes. At $t = 1$ his utility will increase if he was allowed to borrow against their future income $S(e_1)$. Second, recharging in the first period is more expensive since it implies a loss of income, favoring recharges at the en of the day. These two effects are included in the model to approximate two of the channels that explain changes in consumption as airtime loans are introduced: biding liquidity constrains and the convenience effect.

Introduction of airtime loans:

Airtime loans allow the agent to acquire balance in period $t = 1$ without the need to incur in the effort e_1. For simplicity, we assume the agent can freely choose how much to borrow instead of receiving a single loan offer. By agreeing on the loan terms, the agent agrees to pay in next period the full amount plus a fee r: $P_m(1 + r)L$. To repay, the agent must visit an airtime vendor with its associated effort cost e_2.

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 five weeks after a line is activated, to implement a event study design (Athey and Imbens, 2018). This is a special case of a general Difference-in-Differences strategy that has been applied empirically to a wide range of contexts.[22]

Proper identification of post-event eligibility effects depends on several assumptions. The first is a generalized form of parallel trends assumption that requires that in the absence of treatment, treated and control individuals would have maintained a difference similar to the present during the baseline period. 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 most plausible individuals do not have private knowledge about the treatment path, that may 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. 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, 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. There are two requirement to satisfy this condition. The first is that each cohort 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. Second, 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

[22] 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)

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.[23] Additionally, the eligibility criteria and size of the loans does not change over the period studied, and any calendar effects that seasonality might caused 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. 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, as 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 2:

$$y_{i,week} = \alpha + \beta_1 Eligible_i + \mu_i + \lambda_{week} + u_{i,week} \tag{2}$$

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 to summarize 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 for this and all subsequent models use standard errors clustered by individual and week.

This model uses a single post-eligibility indicator $Eligible_i$ for all periods after airtime loans are available.[24] We also include μ_i and λ_{week} to capture individual and calendar-week fixed effects. To properly estimate the calendar week fixed effect we include a random sample of users that have a

[23] As described by Roth (Working Paper), restricting the sample to only customers that do not drop from the sample can induce selective survival bias. However, results hold when we lower the inclusion criteria by allowing customers that drop early from the sample, see 4A

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

long history in the network. Due to data limitations, we do not know precisely when these lines were activated but have been continuously in the network for more than five months. The eligibility of these phone numbers does not change during the period studied and they act as a counterfactual.[25]

A growing literature shows that in case there are heterogeneous treatment effects results from equation 2 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).[26] To account for this, we also estimate a model with coefficients for each week a subscriber is in the sample. Specifically, we estimate:

$$y_{i,week} = \alpha + \sum_{j=-4}^{-2} \beta_k (Lag\ j)_{i,week} + \textstyle\sum_{k=0}^{7} \gamma_k (Lead\ k)_{i,week} + \mu_i + \lambda_{week} + u_{i,w} \tag{3}$$

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 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.

[25] The random sample of customer is twice the size of the sample of new lines.

[26] 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.

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 time, duration and date, as well as the cellular towers that managed it. 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).

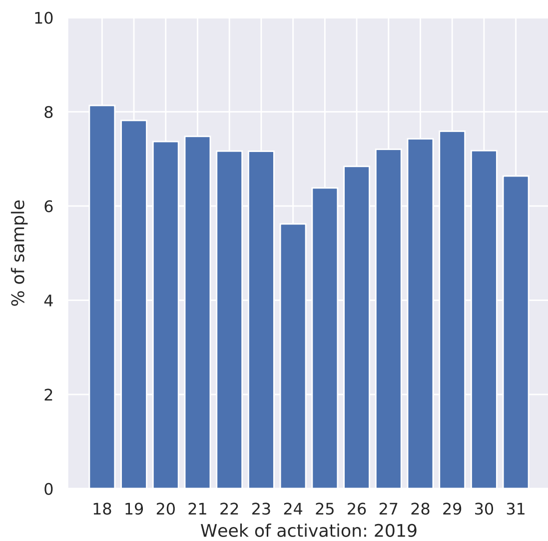
We aggregate the transactions of each customer at the week-level. This makes that, in calendar-year terms, our data covers week 18 to 48 of 2019. To observe how network behaviour changes before and after access to the airtime loans, we focus on new lines activated between May and July 2019 (calendar 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 3a).

Similar to the experience in other settings, there is a large level of subscribers churn (Roessler *et al.*, 2018). Only 39% of new lines remain active when our records stop. 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 3b). Customers that stop using their numbers are free to obtain a new number one without any penalty, however, the eligibility condition still imposes a waiting period of four weeks before the new number can obtain loans.[27] We do not find evidence that a number dropping from the sample correlates with having outstanding loan balance, with only **XXXXX** of the lines dropping from the sample having any outstanding balance.

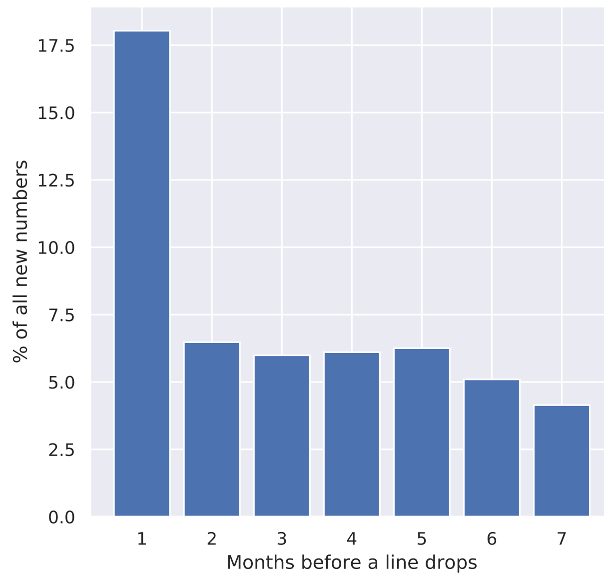
[27] A customer losses ownership of the number if he does not recharge during four consecutive months; in that case, the number can be reassigned. We assign as the last date we stop observing transactions as the day the line was dropped. One additional group that we identify are lines that we classified 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 2A

Figure 3: New lines
May and July 2019

(a) Percentage of new lines during the period



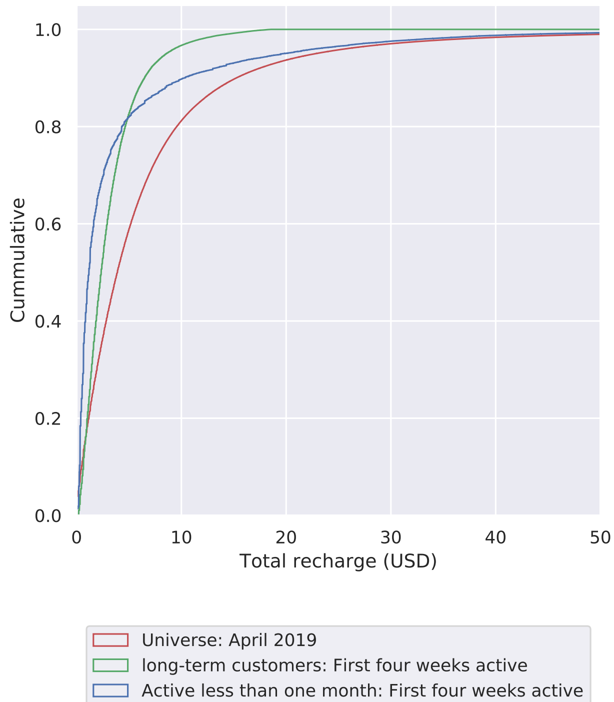
(b) Attrition over time



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

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 ares 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, expenditure from the long-term customers is systematically lower than for the whole universe of well-established line, and tends to be below the expenditure of lines whose activity does not last longer than a month (Figure 4).

Figure 4: CDF cummulative expenditure
Several samples



Note: Universe contains well-established lines that were active at the time when data first became available and remain active during the period.

It is worth noting that all the evaluations of the impact to access to digital credit that we know rely on a regression discontinuity design. This makes their results internally valid on a limited window around the credit score threshold. Individuals on this window tend to have low income levels, which limits how much of the impacts can be read as general results. A similar caveat should be make for our results, considering that new customers appear to come, overall, from low income groups, making us careful not to extrapolate the results from this sample to the overall universe of subscribers, especially to those with higher economic means that adopted early.[28] We add a longer discussion on who new customers are with respect of the overall network in section 6.1

[28] As one would expect as there is still ample room for additional cellphone adoption. For reference, the tail of the expenditure distribution of new long-term customers is below the top 10% of expenditure from the distribution of well-established lines (see Figure 5A for reference).

5 Results

We start by showing the results from equation 2. Table 2 shows the impacts in monetary and as a percentage change with respect to the baseline values before loan availability. Loan access increased expenditure in 16%. 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.[29] 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, post eligibility a customers make 3.7 more calls, but their average duration falls in almost 3 seconds.

Table 2: Impacts credit access
Post-eligibility period

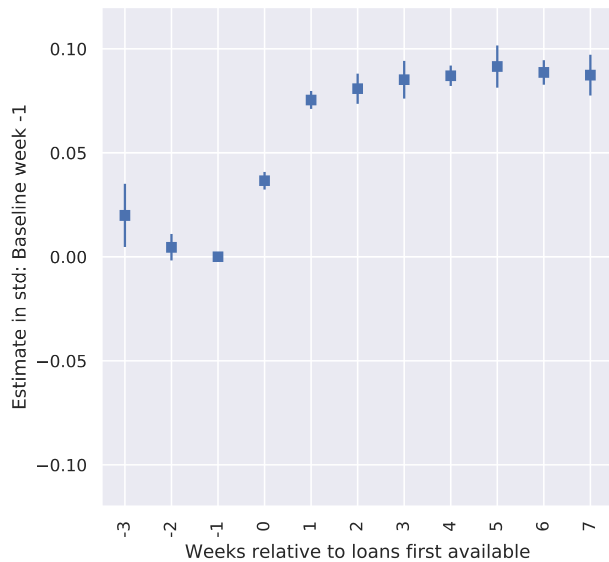
	Expenditure (USD)	Number of recharges	Average recharge (USD)	Outgoing contacts	Outgoing transactions	Average call duration	Gambling expenditure
Baseline	0.92	2.58	0.31	6.74	41.07	74.93	0.59
Effect	0.15***	0.19***	0.01***	0.13*	3.72***	-2.65***	0.01
Δ in percentage	16.07	7.52	3.51	1.97	9.07	-3.53	1.33

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 are the result of estimating equation 3. We find that loan access increases weekly expenditure in a magnitude equivalent to 0.09 standard deviations. 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 5). Figure 6 provides an overview of the key network metrics. The patterns present large variation before and after eligibility. The exception is gambling expenditure where we do not see any impact of access to credit.

[29] Figure 4A in the Appendix shows that results hold when we also include in the sample numbers that dropped 3 months after they were activated.

Figure 5: Total weekly expenditure

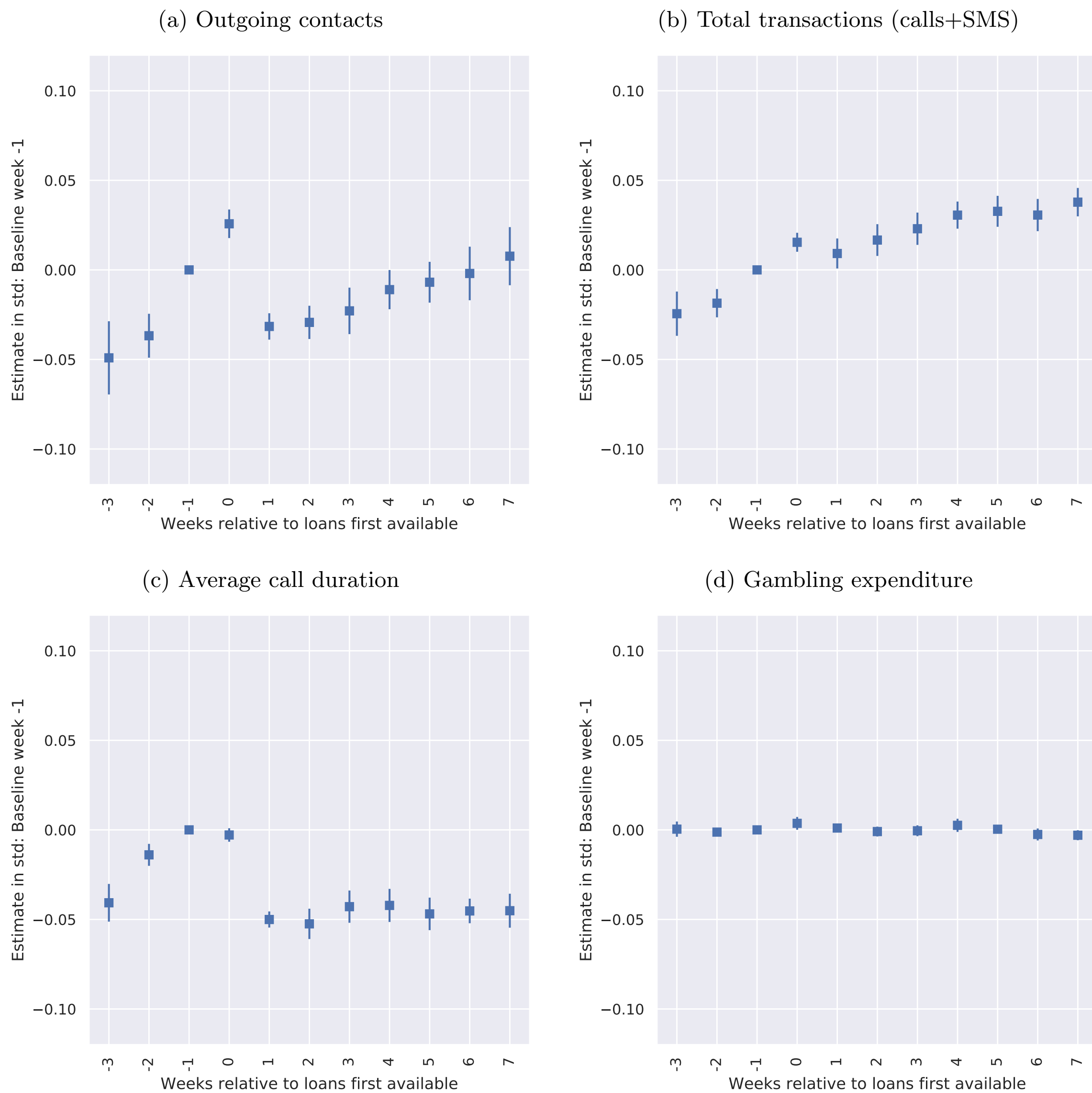


Note: Includes only long-term customers. Loan access is provided at week 0 and the week before is used as baseline.

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 7). 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 data to fully answer this. 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 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.

Figure 6: Key network metric activities
Long-term customers



(a) Outgoing contacts

(b) Total transactions (calls+SMS)

(c) Average call duration

(d) Gambling expenditure

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

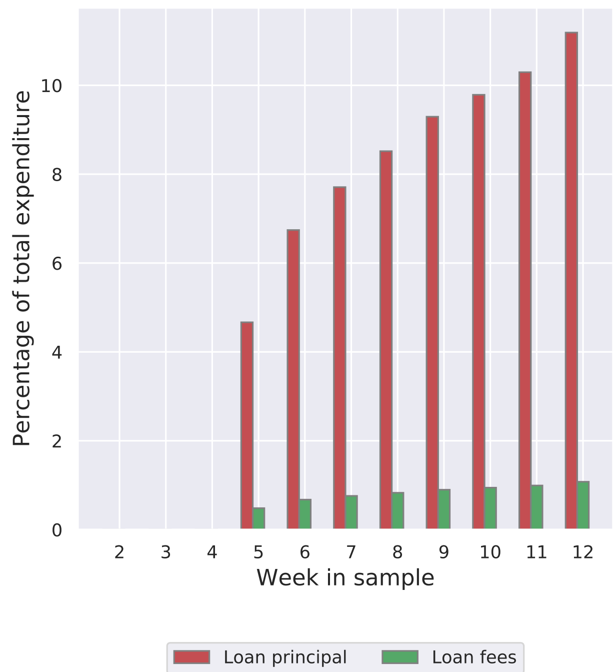
Second, airtime loans reduce the salience of the costs of calls. The process of looking for a street vendor and paying in cash increases the salience of the cost of calls. By allowing instantaneous access to airtime, this self-control mechanism embedded in prepaid disappears (Laibson, 1997; O'Donoghue and Rabin, 1999). Observing an increase in expenditure as the salience of the cost disappears mirrors the impact of switching to prepaid electricity billing, where the change led to a reduction of total consumption (Jack and Smith, 2020).[30]

Third, high transaction costs associated with buying airtime stop consumer from recharging, even when they have the means to acquire it. These transaction costs include the opportunity costs of time that finding an agent needs. Under this mechanism, access to credit eliminates the cost of finding an agent, and increase demand as long as the perceived utility from calling is larger than the cost and the 10% facilitation fee. In turn, customers can modify their recharge patterns across the day towards times when they find it more convenient.

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.

[30]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). Borrowing from the literature that explores the expenditure patterns of the poor, an alternative explanations is agents limiting the amount of credit available at any given time also include storage costs (O'Donoghue, 2020). This does not apply in our setting as airtime credit take a month to expire and can always be transferred to other subscribers.

Figure 7: 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 observe. In this section, we provide empirical evidence of the extend cellphone consumption of the 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: 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 in the expenditure impacts of airtime loans 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 these loans for 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.[31] These applications rely statistical methods to detect the a relation between a socioeconomic indicator and cellphone usage patterns.[32]

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). In an ongoing project, we explore the possibility of replicating the targeting and results of an impact evaluation using cellphone data.

In order to implement these methods it is necessary to be able to link individual characteristics of subscribers with their own cellphone metadata. This requires to survey participants and obtain

[31] 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.

[32] 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.

informed consent on their part to be able to match these two sources of information; a task that customer protection laws tend to impose a high bar for. Best practices for collecting ground true data are properly understood. However, there are still several open questions about how to best exploit the cellphone records and the properties of the prediction models. Specifically, it is a matter of debate how many months of retrospective cellphone records should be used and how fast a model's predictive capability decays as it is used on a different sample, and using different time periods.

Predicting individual income status from cellphone usage requires collecting a survey before subscribers become eligible for airtime loans. In our setting, this is difficult to implement for several reasons linked to the conditions of airtime loans. First, 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. Moreover, from an operation perspective collecting a survey in new subscribers is challenging due to the high levels of early attrition, as it is likely that almost a quarter of the sample drop before they become eligible for the loans, or soon after. Second, the sample that enters the network at different points in time raising 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, an approach that is validated from other studies (Gutierrez *et al.*, 2013). In the next subsection, we build on these results to disentangle heterogeneous effects and the mechanisms behind them. For this, we use a phone surveys representative of the universe of mobile money users.[33] A total of 600 subscribers participated in the survey. 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.[34]

[33]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.

[34]By using a shorter period, we run the risk of omitting the recharges of consumers that recharge a single large

The majority of participants were male and head of their households (61% and 55% respectively). People in our sample are wealthier than the average Haitian, with higher levels of asset ownership. This is expected as phone ownership is a prerequisite to be in the survey. Still, we observe high levels of food insecurity, with 60% reporting skipping meals or reducing portion sizes. With respect to labor market outcome, we find that 40% of participants were employed in the week prior to the survey. This result helps to explain why in our measure of income stability only 10% of people consider their income to be predictable. 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 is well above other forms of credit, with only less than half of participants owning money to other sources. 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 (see Table 1A in the Appendix)

Only for those employed we have information about their income during the week. For this group, we estimate equation 4 to understand how income correlates with total cellphone expenditure, average amount and number of recharges. As one would expect, 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). A similar story can be seen in Figure 8A, where we see that the recharge terciles map to higher levels of income and larger average recharges.[35]

$$y_i = \beta_0 + \beta_1 ln(income)_i + \beta_2 age_i + \beta_3 men_i + \beta_4 Household\ Head_i + \beta_5 Day\ survey_i + u_i \tag{4}$$

deposit a month.

[35]We also check 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 2A)

Table 3: Network transactions and income stability
Phone survey sample

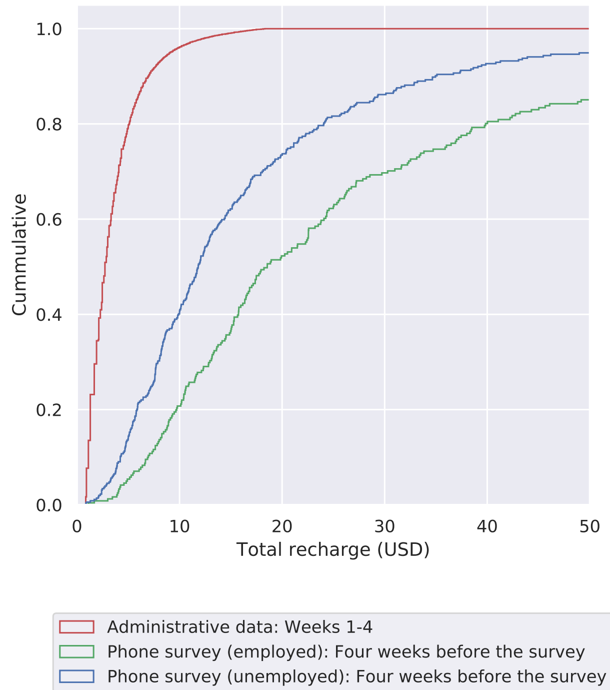
	Recharges		
	Total Recharge (USD)	Average recharge (USD)	Number of recharges
ln(income)	7.74***	17.58**	1.29
	(2.64)	(7.49)	(0.97)
HH of households	6.06	20.02**	-2.42
	(4.68)	(9.34)	(2.52)
gender	4.8	-8.87	6.06***
	(5.86)	(14.47)	(1.94)
age	0.09	0.45	0.05
	(0.27)	(0.56)	(0.11)
const	-43.75**	-73.35	13.17
	(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 8 shows the cumulative distribution of total expenditure for the long-term customers 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 consume more; a gap that new lines seem to close slightly during their second month of activity.

Figure 8: Cumulative distribution of total expenditure
Long-term customers and surveyed sample

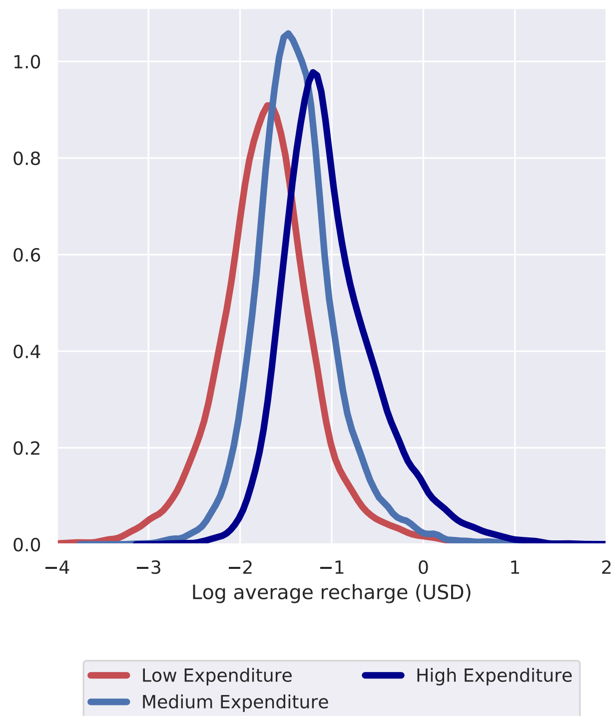


Note: Administrative data contains only long-term customers. Weeks 1-4 represent the first month after activation when airtime loans where not available.

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 3A 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. 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 (9).

Figure 9: Average transaction size (USD)
Long-term customers

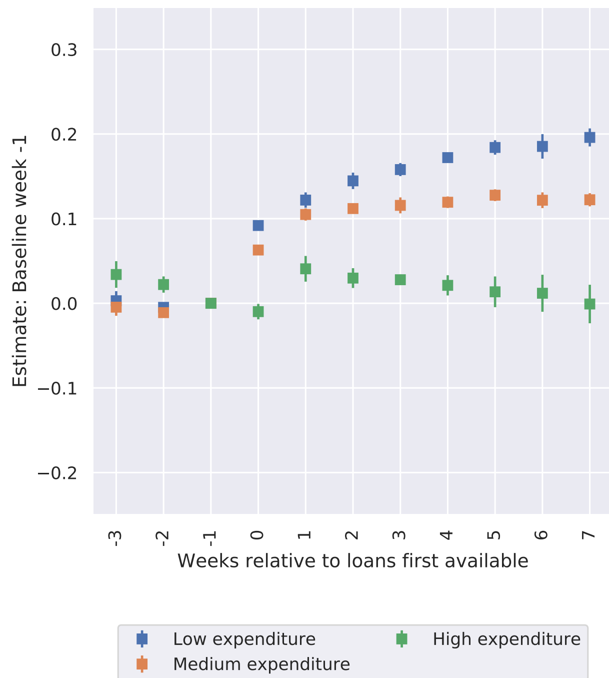


Note: Average transaction size during the initial 4 weeks

Estimating equation 3 for each individual group reveals a high heterogeneity of impacts. A summary of the 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. This increase in expenditure happens soon after loans become 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.[36] Similarly, the medium group experienced an increase of 30 percent in their weekly expenditure, see table 4.

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

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.

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.[37] These differences exist despite the groups having relative uniform patterns of loan usages. 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 5).[38]

[37] Figure 6A shows estimations at the week-level for key network variables.

[38] Table 4A shows the share of total expenditure financed with loans each week. For details on the probability of borrowing each week see Figure 3A in the Appendix.

Table 4: Table with 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	0.95	0.74***	77.7	2.48	0.2***	7.93	4.02	-0.27***	-6.7
Avg. recharges (USD)	0.14	0.07***	49.79	0.25	0.03***	10.42	0.47	-0.03***	-6.82
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	0.3	0.17***	54.25	0.5	-0.02	-3.48	0.68	-0.05**	-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 5: 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. Better off groups still have a high demand for loans but their total expenditure remains unchanged. We argue that this group relies on loans for their convenience factor. In the next section, we further explore these channels.

6.3 Heterogeneous Motivations for Using Airtime Loans

In this section, we revisit the mechanisms that explain how credit access increases cellphone expenditure. The first mechanism consists on credit access relaxing binding liquidity constraints. In the context we study, it is not surprising that large imperfections in the credit market makes consumption patterns extremely sensitive to the cash available at any point in time. This sensitivity is increased via precautionary savings in the cases when, in addition, there is uncertainty on future income.

Our results show that inline with the existence of a liquidity constrain, only poor customers experience an increase in their expenditure levels once credit access is granted. People in these group are more likely to have a high perceived value of holding cash during the day as they tend to depend on the informal economy. 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.

To understand the role convenience on demand for airtime loans, we explore for changes in the recharge patterns. For this, we build on the fact that we are able to observe the precise timing of every recharge transactions. 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 9A A and C).

We think of convenience in two different ways, that we call external and internal. External convenience is when airtime loans allow a customer to recharge in cases where the options to do so are objectively difficult. This is the case late at night, for example. Internal convenience is when the recharge options are available, but a customer with enough cash considers prefers to use the airtime loan, pay loan facilitation-fee, and recharge later.

With respect to external convenience, we find that when recharging opportunities are low, the volume of airtime loans with respect to recharges reaches its peak. 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 without statistically significant differences bet wen them (Figure 11B and D).[39]

The second, and more interesting, type of convenience, is when airtime loan usage allow con-

[39] Figure 10A presents the same results but by number of transactions per hour

sumers to strategically change their 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 customer become eligible using equation 5. Our coefficient of interest is the interaction between the hour dummy and the indicator if a customer is eligible for the credit product.[40]

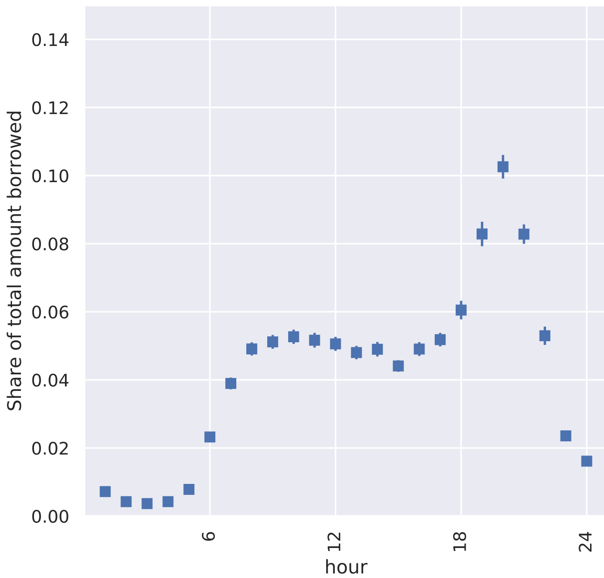
To understand results from Figure 5, it is important to remember that airtime loans eligibility reduces the number of recharge transactions for the non-poor, with the opposite effect on the poor. Moving to Figure 5, we see that the reduction in the number of recharges for the non-poor is particularly marked in the recharges that happen after 7pm, a time of the day where 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.

$$\begin{aligned} recharge_{i,day,hour} = \alpha + \sum_{h=1}^{24} \beta_h hour_{i,day} + \gamma Eligible_i + \sum_{h=1}^{24} \beta_h hour_{i,day,hour} \times Eligible_i + \\ \mu_i + \lambda_{week} + u_{i,day,hour} \end{aligned} \tag{5}$$

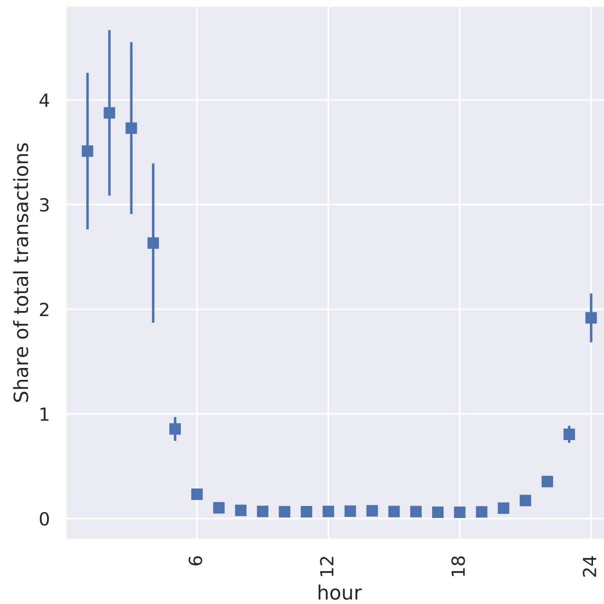
[40] This estimation requires that we have a dataset that indicates for each customer if a recharge transaction happened at any hour of the day. As the memory requirement grows exponentially, we use a random sample with a third of the original subscribers, and aggregate the transactions between midnight 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

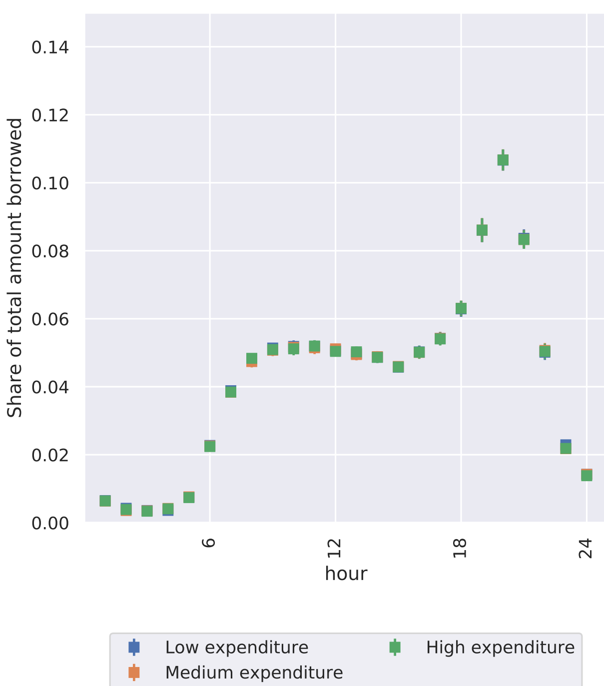
(a) Amount borrowed



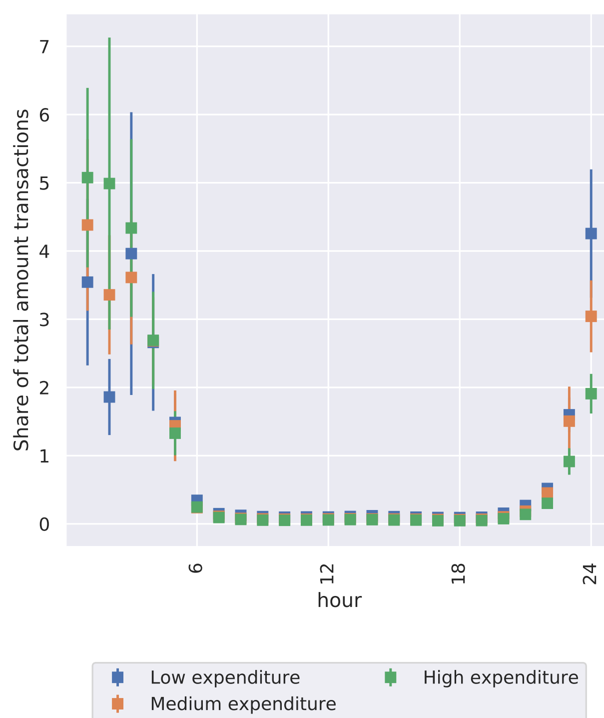
(b) Amount borrowed over amount recharged



(c) Amount borrowed
by initial expenditure tercile

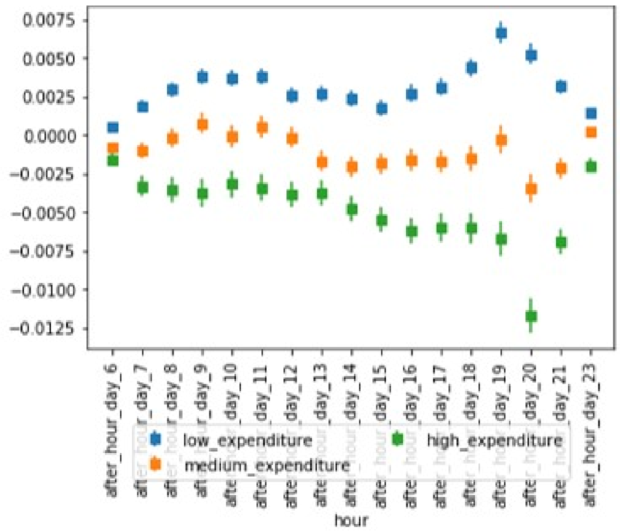


(d) Loan transactions over recharges transactions
by initial expenditure tercile



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 lenders. MFS introduces innovations that allow it reach these groups. By using alternative credit screening methods, and an application process and delivery of funds that relies exclusively on the infrastructure already in place by cellphone companies. The pace of development of new products is linked to how many of these features the product uses, as the level of risk and know-how increases with how innovative the product is. Fully digital loans have had a slow pace of adoption when we compare them to products that only use cellphones as an interface, but that are provided by traditional lenders. The effectiveness of products in this intermediate tier to provide credit access to lower income populations is up for debate, and it should not be expected that a single product can fit the needs of every consumer. Nevertheless, it is difficult to think that products that depend on physical locations and bank accounts can be easily became attractive in areas where banking and other infrastructure is limited. Airtime loans is leading the way to make MNO more comfortable with providing fully digital loans. Leveraging the reach of the infrastructure of cellphone companies gives it the possibility to reach most segments of society. 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 results confirm that credit market failures are widespread, and that they have a negative effects on cellphone expenditure in groups with biding liquidity constrains. Based on our findings, people are not able to adjust their communication consumption using the saving and informal credit methods available to them, making them extremely sensitive to the timing of their income. 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. We lack the data to test this. 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), and (Blumenstock *et al.*, 2016).

Second, more research is necessary to understand the extend convenience and liquidity constrains contribute to the demand of digital credits, and its implications on the welfare effects of loan demand. In particular, how loan affect groups with lower levels of vulnerability. Our results suggest that the strength of latter mechanism decreases with income. However, all the studies of digital credit have identification constrains that make their results internally valid only to populations with low income levels and very low access to other credit substitute. However, demand for credit is not unique to these groups, and the welfare implications (and demand levels) for better-off customer need to be studied. From the previous discussion about how loan demand is driven by factors other than liquidity, and interesting area of study is the role of gender in loan demand. There is evidence that women have usage-signatures that can be detected from the mobile data

(Al-Zuabi *et al.*, 2019; Sarraute *et al.*, 2014), and that they suffer from higer levels of liquidity constrains as well as security considerations. These two elements can drive a demand that is specific to women, that should be studied.

Third, airtime loans is a first step towards using MFS for financial inclusion. The low amounts involved are an advantage as the allow 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. These risk involve harmful long-term effects of overindebetdness, and being deny future formal credit options as a results of default. 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, continue research on digital credit must continue in order to improve the screening of customers, manage trade-offs between accuracy and fairness, improve consumer protection policies, and create better channels and methodologies to guarantee that customers are fully informed of the costs of credit and their conditions.

References

Agüero, A., de Silva, H. and Kang, J. (2011). Bottom of the pyramid expenditure patterns on mobile services in selected emerging asian countries. *Information Technologies International Development*, **7** (3), 19–32.

Aker, J. C. and Mbiti, I. M. (2010). Mobile phones and economic development in africa. *Journal of Economic Perspectives*, **24** (3), 207–32.

Al-Zuabi, I. M., Jafar, A. and Aljoumaa, K. (2019). Predicting customer's gender and age depending on mobile phone data. *Journal of Big Data*, **6** (1), 18.

Aron, J. *et al.* (2017). *'Leapfrogging': A survey of the nature and economic implications of mobile money*. Tech. rep., Centre for the Study of African Economies, University of Oxford.

Athey, S. and Imbens, G. W. (2018). *Design-based analysis in difference-in-differences settings with staggered adoption*. Tech. rep., National Bureau of Economic Research.

Attanasio, O. and Frayne, C. (2006). Do the poor pay more?

Ausubel, L. M. (1991). The failure of competition in the credit card market. *The American Economic Review*, **81** (1), 50–81.

Bharadwaj, P., Jack, W. and Suri, T. (2019). *Fintech and Household Resilience to Shocks: Evidence from Digital Loans in Kenya*. Working Paper 25604, National Bureau of Economic Research.

Björkegren, D., Blumenstock, J. E. and Knight, S. (2020). Manipulation-proof machine learning.

— and Grissen, D. (2018). The potential of digital credit to bank the poor. *AEA Papers and Proceedings*, **108**, 68–71.

Blumenstock, J., Cadamuro, G. and On, R. (2015). Predicting poverty and wealth from mobile phone metadata. *Science*, **350** (6264), 1073–1076.

Blumenstock, J. E. (2018). Estimating economic characteristics with phone data. In *AEA papers and proceedings*, vol. 108, pp. 72–76.

—, Eagle, N. and Fafchamps, M. (2016). Airtime transfers and mobile communications: Evidence in the aftermath of natural disasters. *Journal of Development Economics*, **120**, 157 – 181.

Bond, P., Musto, D. K. and Yilmaz, B. (2009). Predatory mortgage lending. *Journal of Financial Economics*, **94** (3), 412–427.

Buchak, G., Matvos, G., Piskorski, T. and Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, **130** (3), 453 – 483.

Bulando, A., Kuhn, M. and Prina, S. (2020). *Digital Credit Delivery Speed and Repayment Rates*. Working paper, University of Oregon.

Callaway, B. and Sant'Anna, P. H. (2018). Difference-in-differences with multiple time periods and an application on the minimum wage and employment. *arXiv preprint arXiv:1803.09015*.

Carlson, S. S. L. (2018). *Essays in financial innovation and development*. Ph.D. thesis, Massachusetts Institute of Technology.

Carrell, S. and Zinman, J. (2014). In harm's way? payday loan access and military personnel performance. *The Review of Financial Studies*, **27** (9), 2805–2840.

Clarke, D. and Schythe, K. (2020). Implementing the panel event study.

Cook, T. and McKay, C. (2015). Top 10 things to know about m-shwari. *CGAP Blog*.

FinScope (2018). Finscope: Consumer survey highlights, haiti. https://http://finmark.org.za/wp-content/uploads/2019/04/Haiti_French_17-04-2019.pdf, accessed: 2020-09-21.

Francis, E., Blumenstock, J. and Robinson, J. (2017). Digital credit: A snapshot of the current landscape and open research questions. *CEGA White Paper*, pp. 1739–1776.

Frias-Martinez, V., Soguero-Ruiz, C., Frias-Martinez, E. and Josephidou, M. (2013). Forecasting socioeconomic trends with cell phone records. In *Proceedings of the 3rd ACM Symposium on Computing for Development*, pp. 1–10.

—, Soto, V., Virseda, J. and Frias-Martinez, E. (2012). Computing cost-effective census maps from cell phone traces. In *Workshop on pervasive urban applications*.

Gelman, M., Kariv, S., Shapiro, M. D., Silverman, D. and Tadelis, S. (2014). Harnessing naturally occurring data to measure the response of spending to income. *Science*, **345** (6193), 212–215.

Gething, P. W. and Tatem, A. J. (2011). Can mobile phone data improve emergency response to natural disasters? *PLOS Medicine*, **8** (8), 1–2.

Goodman-Bacon, A. (2018). *Difference-in-differences with variation in treatment timing*. Tech. rep., National Bureau of Economic Research.

Gross, D. B. and Souleles, N. S. (2002). Do liquidity constraints and interest rates matter for consumer behavior? evidence from credit card data. *The Quarterly journal of economics*, **117** (1), 149–185.

GSMA (2014). *State of the Industry: Mobile Financial Services for the Unbanked*. Tech. rep., GSMA.

— (2019). *The Mobile Gender Gap Report 2019*. Tech. rep., GSMA.

Gutierrez, T., Krings, G. and Blondel, V. D. (2013). Evaluating socio-economic state of a country analyzing airtime credit and mobile phone datasets. *arXiv preprint arXiv:1309.4496*.

Jack, K. and Smith, G. (2020). Charging ahead: Prepaid metering, electricity use, and utility revenue. *American Economic Journal: Applied Economics*, **12** (2), 134–68.

Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the south indian fisheries sector. *The quarterly journal of economics*, **122** (3), 879–924.

Karlan, D. and Zinman, J. (2010). Expanding credit access: Using randomized supply decisions to estimate the impacts. *The Review of Financial Studies*, **23** (1), 433–464.

Khan, M. R. and Blumenstock, J. E. (2016). Predictors without borders: behavioral modeling of product adoption in three developing countries. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 145–154.

Lu, X., Bengtsson, L. and Holme, P. (2012). Predictability of population displacement after the 2010 haiti earthquake. *Proceedings of the National Academy of Sciences*.

McKinsey (2017). Fintech: Opportunities and challenges for banks and regulators.

Morse, A. (2011). Payday lenders: Heroes or villains? *Journal of Financial Economics*, **102** (1), 28–44.

O'Donoghue, B. D. J. D. W. T. (2020). *Paying More for Less: Why Don't Households in Tanzania Take Advantage of Bulk Discounts?* The World Bank.

Roessler, P., Myamba, F., Carroll, P., Jahari, C., Kilama, B. and Nielson, D. L. (2018). Mobile-phone ownership increases poor women's household consumption: A field experiment in tanzania. In *Proceedings of the Evidence in Governance and Politics Meeting, Nairobi, Kenya*, pp. 1–15.

Roth, J. (Working Paper). Pre-test with caution: Event-study estimates after testing for parallel trends.

Sarraute, C., Blanc, P. and Burroni, J. (2014). A study of age and gender seen through mobile phone usage patterns in mexico. In *2014 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM 2014)*, IEEE, pp. 836–843.

Skiba, P. M. and Tobacman, J. (2019). Do payday loans cause bankruptcy? *The Journal of Law and Economics*, **62** (3), 485–519.

Sun, L. and Abraham, S. (2020). *Estimating dynamic treatment effects in event studies with heterogeneous treatment effects*. Tech. rep., Working Paper.

Suri, T. (2017). Mobile money. *Annual Review of Economics*, **9**, 497–520.

— and Jack, W. (2016). The long-run poverty and gender impacts of mobile money. *Science*, **354** (6317), 1288–1292.

The World Bank (2012). *Mobile Usage at the Base of the Pyramid in Kenya*. Tech. rep., iHub Research and Research Solutions Africa.

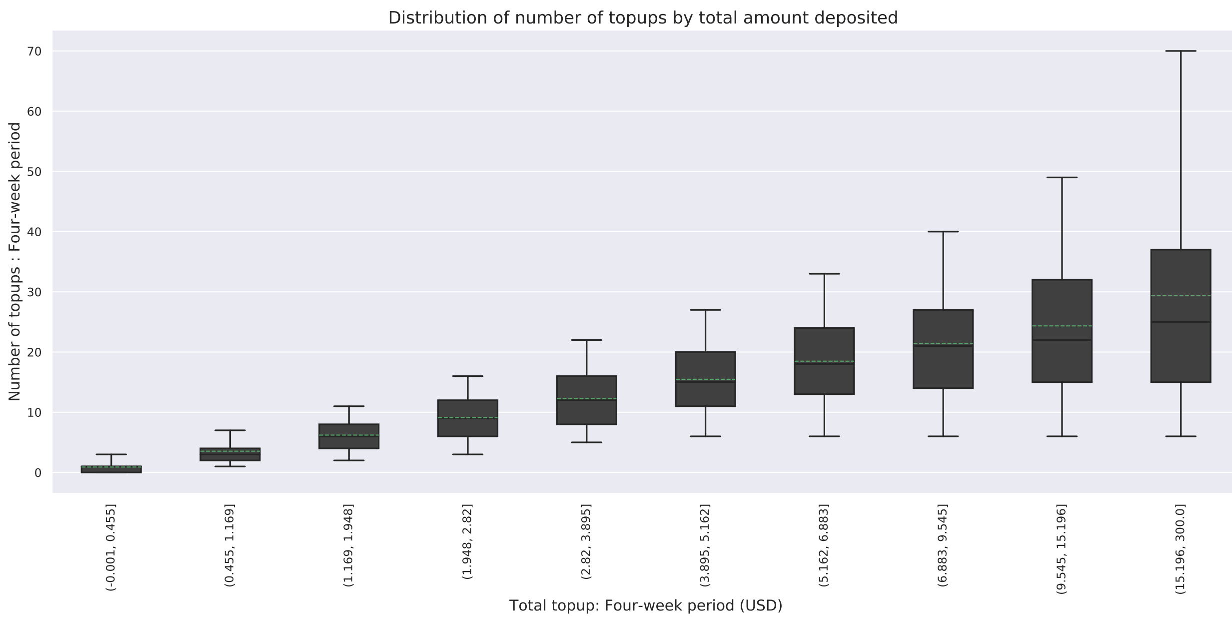
The World Bank (2020). Haiti, poverty and equity brief. https://databank.worldbank.org/data/download/poverty/33EF03BB-9722-4AE2-ABC7-AA2972D68AFE/Global_POVEQ_HTI.pdf, accessed: 2020-09-21.

Zagatti, G. A., Gonzalez, M., Avner, P., Lozano-Gracia, N., Brooks, C. J., Albert, M., Gray, J., Antos, S. E., Burci, P., zu Erbach-Schoenberg, E., Tatem, A. J., Wetter, E. and Bengtsson, L. (2018). A trip to work: Estimation of origin and destination of commuting patterns in the main metropolitan regions of haiti using cdr. *Development Engineering*, **3**, 133 – 165.

Zinman, J. (2010). Restricting consumer credit access: Household survey evidence on effects around the oregon rate cap. *Journal of banking & finance*, **34** (3), 546–556.

8 Appendix

Figure 1A: 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 2A: Time in the network
New numbers May and July 2019

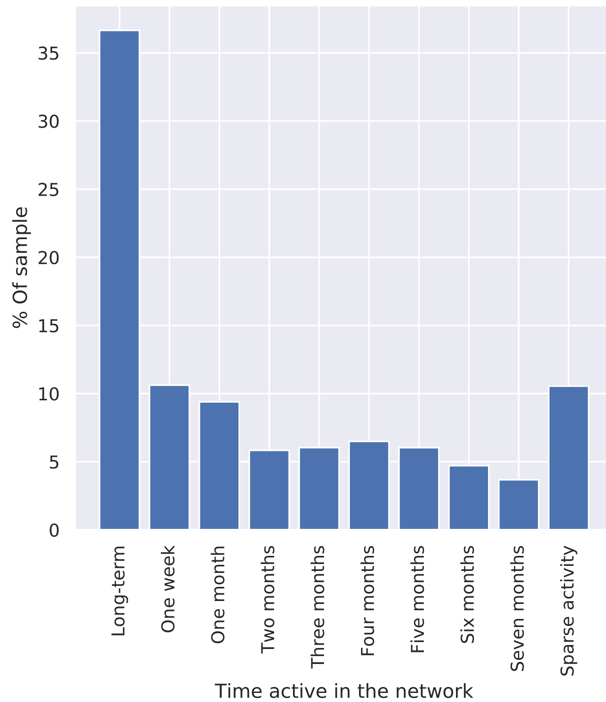


Figure 3A: Percentage of each group using airtime loans each week

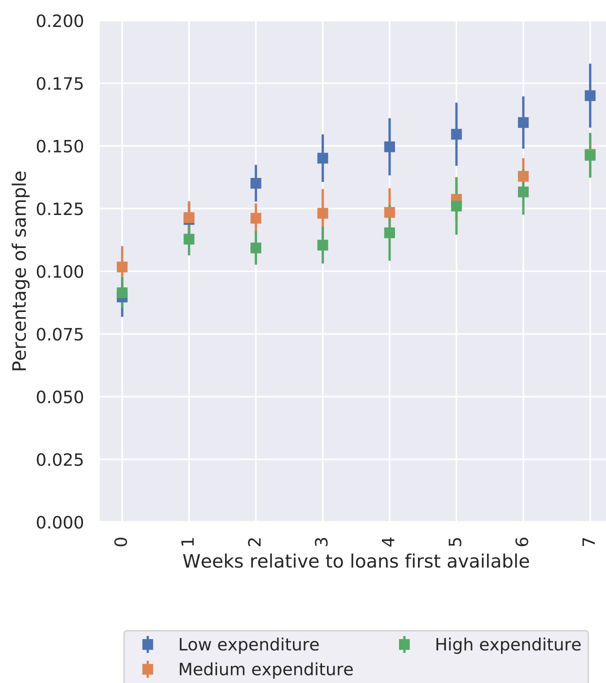
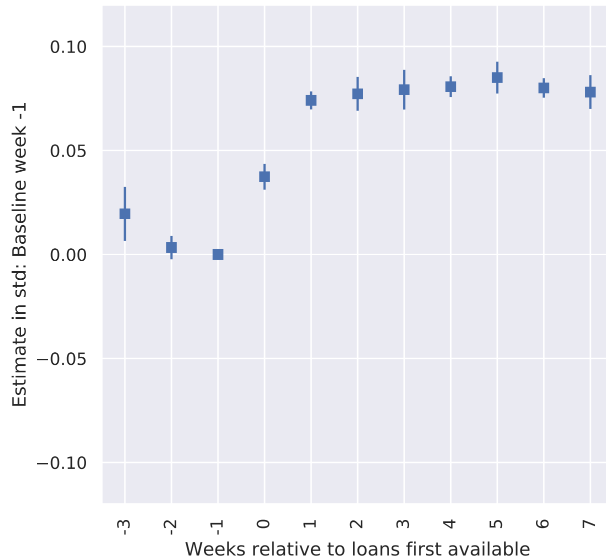
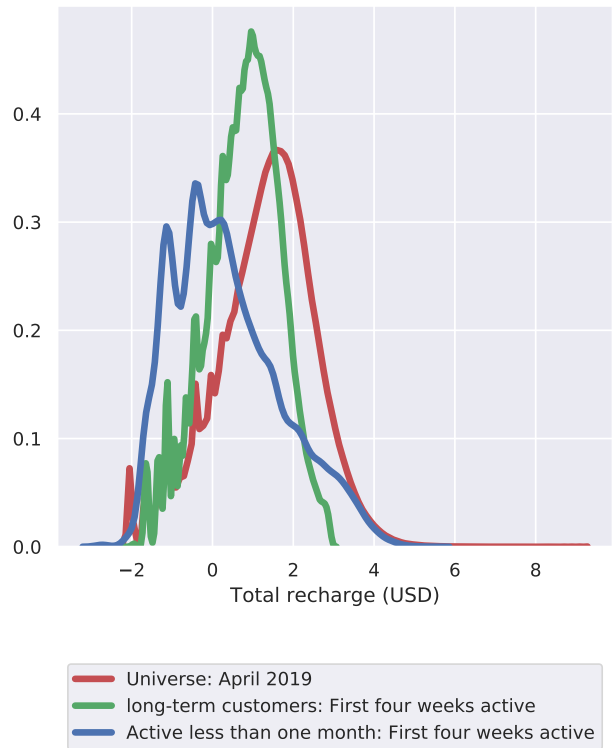


Figure 4A: All new customers more than 3 month active
Total weekly expenditure



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 5A: PDF cummulative expenditure
Several samples



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

Table 1A: 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)	3.69	5.51	0.04	0.31	2.04	10.2	40.82
Family	0.2	0.4					
Amount (USD)	5.9	19.42	0.11	0.53	2.04	9.59	153.47
Bank	0.07	0.25					
Amount (USD)	140.35	691.48	0.51	3.78	20.41	67.35	4285.71
Shopkeeper	0.04	0.2					
Amount (USD)	1.43	2.26	0.1	0.19	0.38	5.82	7.14
Informal	0.02	0.14					
nan	3.37	2.28	0.31	0.41	3.06	5.69	7.14

Note: Includes 589 survey participants with matched cellphone records.

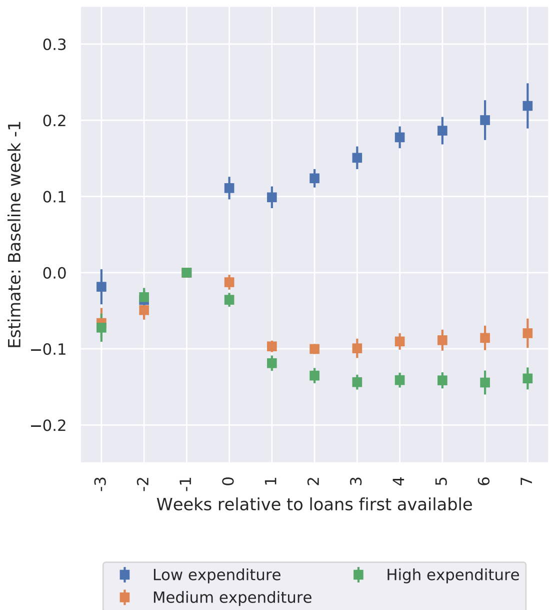
Table 2A: Network transactions statistics
Four weeks prior to survey

	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

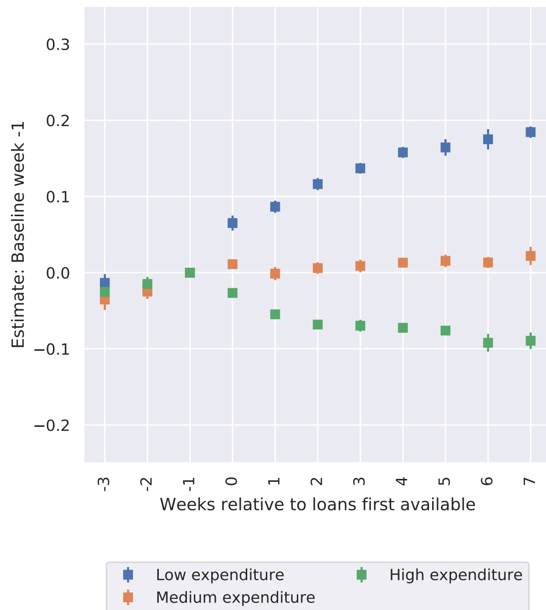
Note: Includes 589 phone survey participants that match cellphone records. Descriptive statistics on cellphone data include one month of mobile transactions.

Figure 6A: Heterogeneous impacts
Key network metric activities

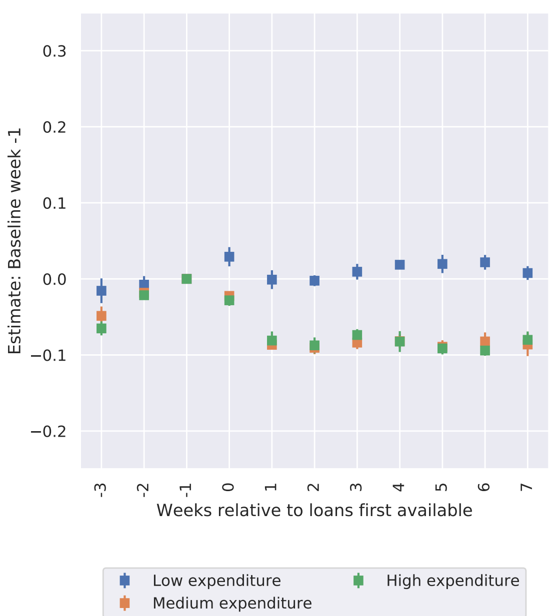
(a) Total number of contacts per week



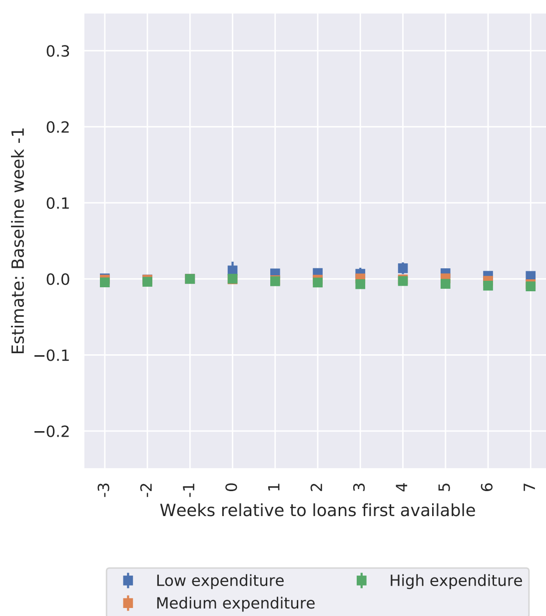
(b) Total outgoing transactions per week (calls+SMS)



(c) Average duration of calls



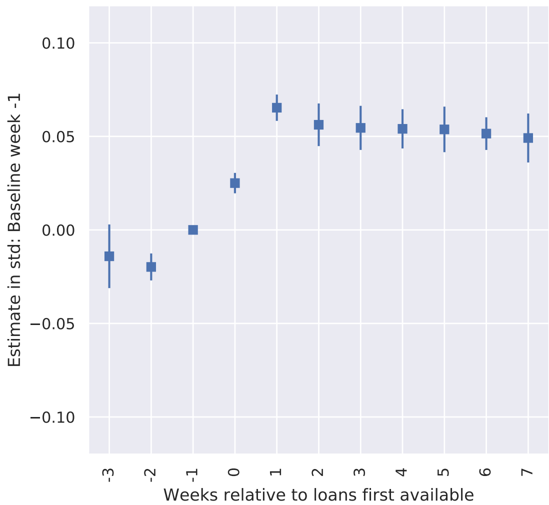
(d) Total expenditure in gambling



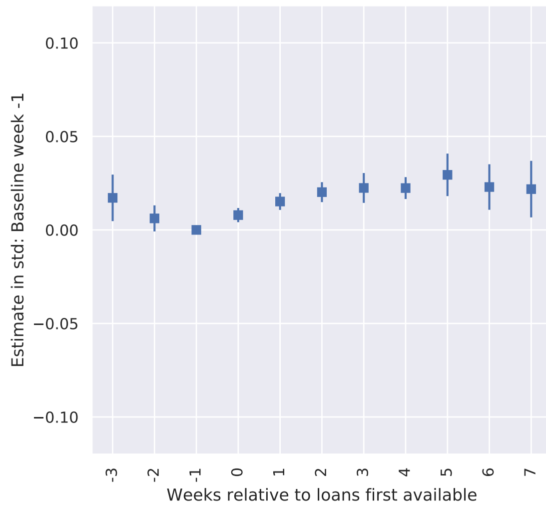
Note: Includes only long-term customers. Results are in standard deviations and use week -1 as baseline.

Figure 7A: Additional results on recharges: Frequency and and amount

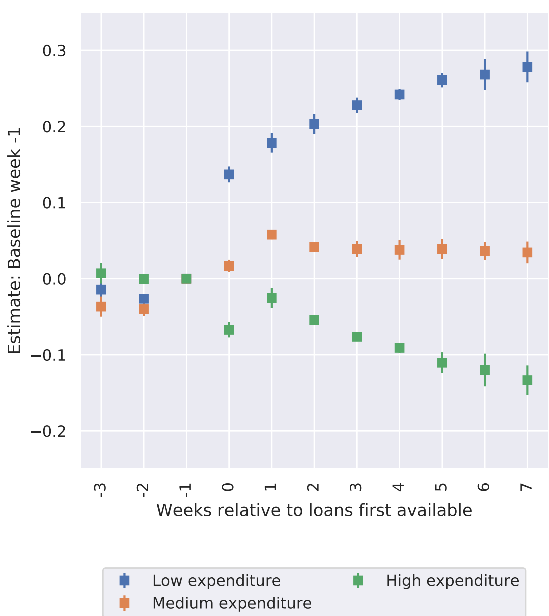
(a) Number of recharge transactions



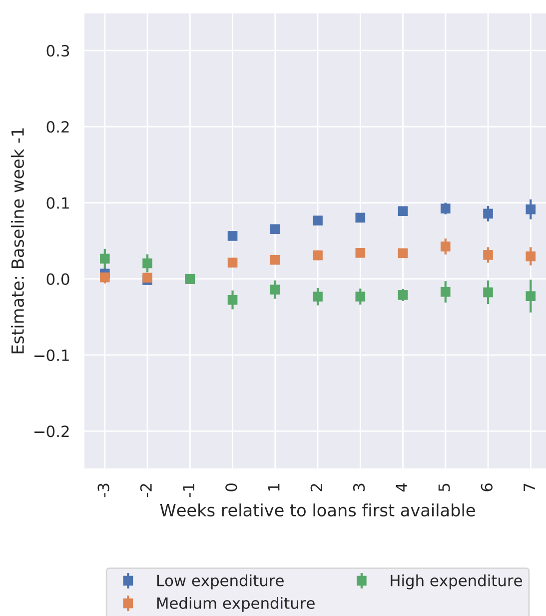
(b) Average recharge amount



(c) Number of recharge transactions: By group



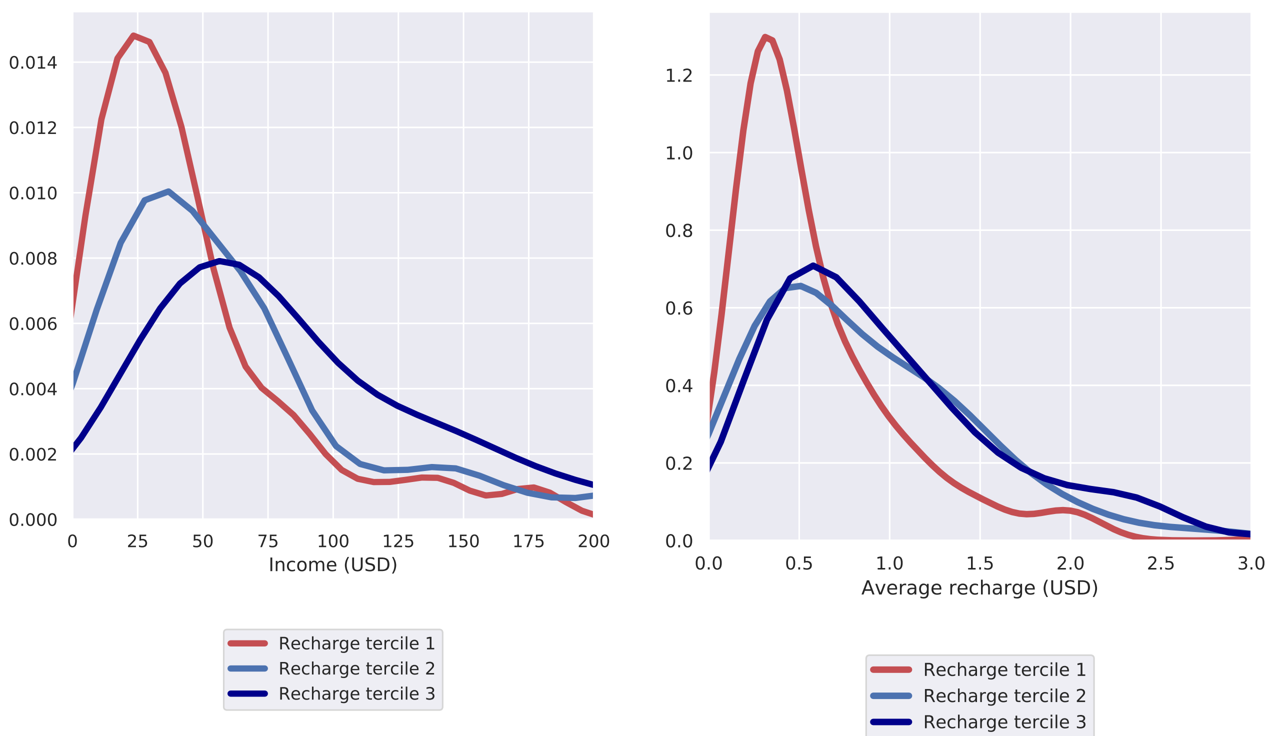
(d) Average recharge amountBy group



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

Figure 8A: Recharge terciles and observed income
phone survey participants only

(a) Reported income (USD) (b) Average recharges



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.

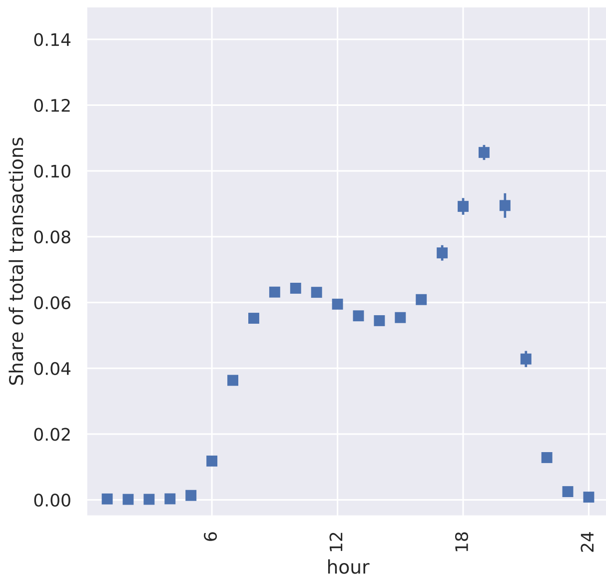
Table 3A: Total Expenditure before loans are available (USD)
Long-term customers

	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

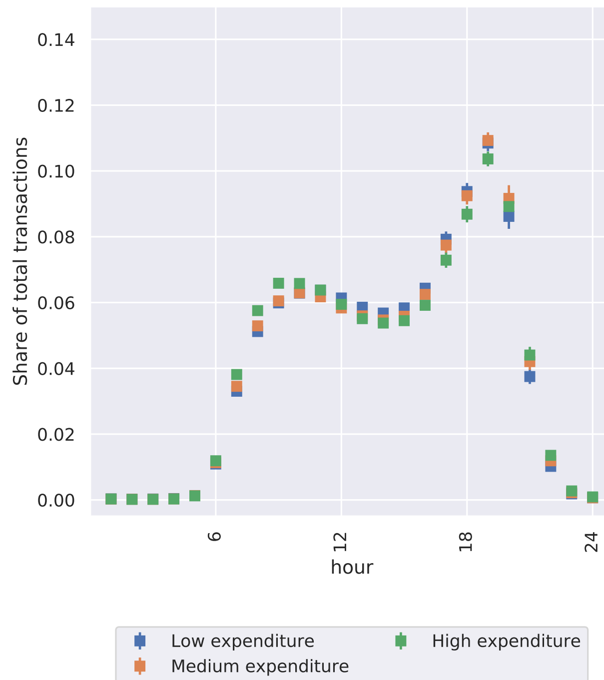
Notes: Includes all the recharge transactions during the first four weeks. As we use terciles of the total expenditure the number of people in each group is very similar.

Figure 9A: Share of total recharge per hour
Long-term customers

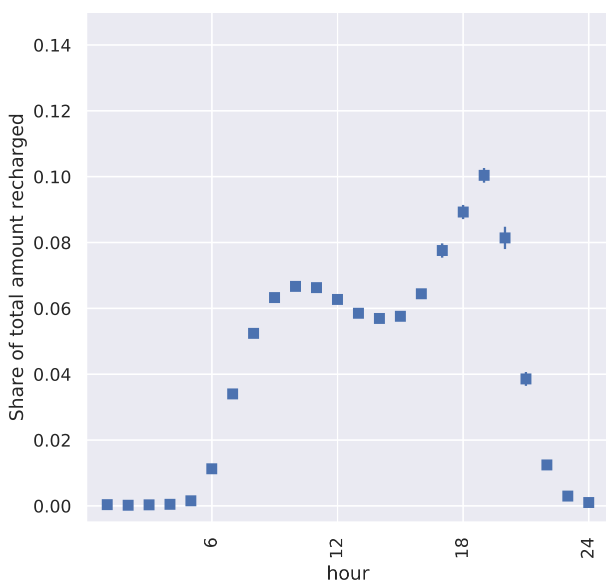
(a) Total number of recharges



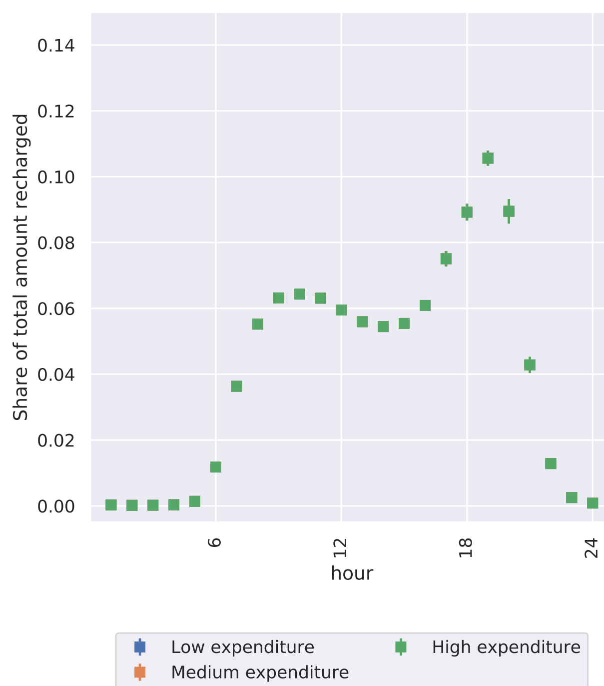
(b) Total number of recharges: Initial tercile expenditure



(c) Total amount recharged

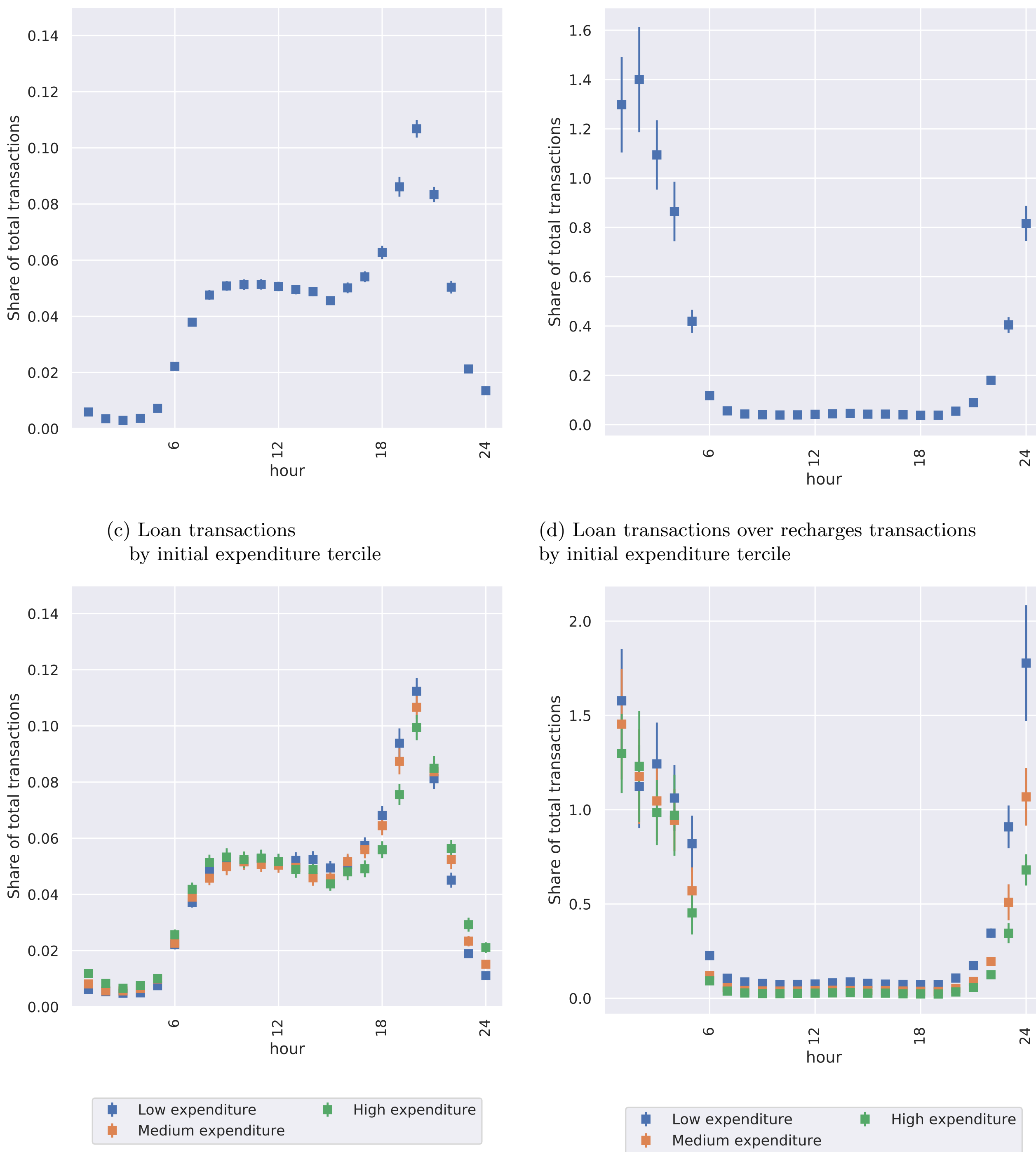


(d) Total amount recharged: Initial tercile expenditure



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 10A: 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.

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

Week	Principal						Facilitation fee					
active	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