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DIGITAL INNOVATION AND REGULATION OF FINANCIAL MARKETS IN ARGENTINA

Baratuche, Stefano

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Digital Innovation and Regulation of Financial Markets in Argentina

Stefano Baratuche

A Dissertation
Presented to the Faculty
of Princeton University
in Candidacy for the Degree
of Doctor of Philosophy

Recommended for Acceptance by
the Department of
Economics
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Abstract

This dissertation examines recent developments in the regulation of financial markets facing consumers and small businesses in Argentina, and the introduction of new products which are in part enabled by these policies.

In the first chapter, I study the design of policies by the local government which targeted Visa, the largest payment card network in the country, operating through a decentralized collective of banks which exhibited notable concentration and vertical integration in the supply of consumer and merchant services. To address this situation, the government combined interchange fee caps with a mandate to divest the largest bank association in this market. I develop a model of bank competition for payment intermediation to argue that interchange fee limits alone would have increased the market share of the leading association, with ambiguous price effects, and show that prior to its divestment it was able to increase consumer charges in excess of local competitors without adverse effects in transaction volume.

The second chapter covers the entry of a big tech platform into the financial intermediation market. Its offering combines payment services with an online loan program for affiliated merchants, with which it supplies risky borrowers on the fringe of access to banking products. I show that this product substantially increased borrowing in this population and caused a concurrent increase in revenue of 10 to 25%. I develop a model of retailers with scarce working capital to highlight the significance of increased access to credit, as well as the possibility of information asymmetries forming around a merchant's markup, sales volume and balance sheet. Estimated merchant credit demand exhibits a positive latent correlation with revenue, indicating advantageous selection conditional on prior screening by the platform.

The third chapter is motivated by a positive correlation between loans formed on this platform and those originating in the banking sector, despite their competition. I show that the platform's entry causes a significant improvement in the credit history of affected merchants, raising credit bureau scores by up to a quartile of their distribution, which may capture an information spillover to other lenders and result in improved loan terms.

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My doctoral studies would not have been possible without the continual support of faculty, peers, friends and family. Their presence made this an experience as enjoyable as it was edifying.

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Lectures and advice from multiple professors have driven my interest in Economics in general, as well as in the research topics I pursued in depth. Comments from Natalie Cox, Adam Kapor, Ernest Liu, Alessandro Lizzeri, Leon Musolff, Chris Neilson, Daniel Paravisini and participants of the Princeton IO Workshop helped me greatly refine my dissertation. Juan Pablo Xandri's generous advice informed my study and research efforts from the beginning of the doctorate. The faculty of Universidad Torcuato Di Tella equipped me with the passion and much of the knowledge that supported my work. In particular, Leandro Arozamena, Emilio Espino and Andrés Neumeyer continued to provide valuable comments throughout my doctoral studies. The domain expertise of Laura D'Amato, Gastón Repetto and other economists from the Central Bank of Argentina bolstered chapter 1 of this dissertation. I also thank project managers and analysts from the Argentine marketplace and lending platform that provided data and institutional details for the analysis contained in chapters 2 and 3. A collaboration with Jeffrey Sun and Vita Titl broadened the scope of my academic interests and expertise.

The company of friends and peers was a pillar of my doctoral experience, within and beyond academic confines. Bruno Baranek, Riccardo Cioffi, Emily Cuddy, and Pellumb Reshidi have each sustained my work and personal well-being in ways that are difficult to summarize in words. George Sorg-Langhans, Parth Parihar, Simon Schmickler and Max Vogler defined many of the moments that I will treasure from the PhD. Office A18 is a wellspring of ideas that I hope I con-

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Princeton University and its Economics department provided financial support to my studies. I am very thankful to the generous and patient Princeton staff which contributed administrative, medical and career development services. Foremost among them, Laura Hedden's single-handed efforts paved the way for much of my progress throughout the PhD.

A mis padres, Elba y Oscar.

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Chapter 1

Pass-through Along the Fee Structure of Payment Cards*

1.1 Introduction

Payment card networks, especially those jointly operated and governed by numerous entities like VISA and MasterCard, have been the subject of extensive inquiry by antitrust agencies and researchers alike. The former are often concerned with the fact that would-be competitors, such as two banks issuing VISA cards to consumers, coordinate to decide part of the market's price structure [1], while the latter have repeatedly attempted to determine whether the outcomes of this process can be improved upon with simple regulation in a manner that is robust to modelling assumptions [2]. At the heart of these and related discussions is the interchange fee, a rate that the bank which issued a purchasing consumer's card charges to the bank (or a related entity) where

*I am grateful to Andres Neumeyer, Laura D'Amato and Gaston Repetto for guidance during a research visit to the Central Bank of Argentina (BCRA). Caetano de Campos Lopes and Martin Gerschenfeld explained in detail recommendations and analysis by the local antitrust agency (CNDC), while professors Ozlem Bedre-Defolie and Emilio Calvano swiftly answered my inquiries about their research. Financial support from Princeton University is gratefully acknowledged.

[1] Evans and Schmalensee (2005b) provides an extensive account of the history of payment card systems, some innovations at the turn of the 21st century, and a discussion of prevailing economic analysis and antitrust regulation at the time.

[2] Initial instances of work written in the key of modern two-sided market models include Rochet and Tirole (2002), Schmalensee (2001), Wright (2003)

the merchant awaiting payment holds its account. It is usually argued that this fee is necessary for intervening banks to internalize demand forces from both consumers and merchants, a balancing act common to all multi-sided markets.

Regulators were not deterred by this argument, however, and on occasion have mandated levels and caps for these fees. Regulation II of the Dodd-Frank Act halved the level of interchange fees for debit card transactions in the United States starting on 2010; the Reserve Bank of Australia similarly capped credit card interchange in 2002; and as late as 2015 the European Commission limited interchange fees for both credit and debit cards to 0.3% and 0.2% of transaction price respectively. As will be discussed below, only payment systems where the issuing and the acquiring bank differ entail the payment of an interchange fee: fully integrated networks, like American Express and Sears's Discover, need no such compensation. This has resulted in asymmetric effects across markets, ranging from the availability of different card types, the level of fees and rewards provided, and pass-through rates to consumer prices. The remainder of the introduction offers a quick overview of the typical market structure of a payment card system, together with some idiosyncrasies of the Argentinian market that present a case of an effectively closed loop network being opened.

1.1.1 Brief description of payment card networks

Economic analysis[3] of payment card markets commonly describes them as a four-party system, consisting primarily of a *consumer*, a *merchant* who engages in a transaction with her, an *issuer* who provides the consumer with a payment card and an *acquirer*[4] who facilitates the merchant's access to the card network and eventually finalizes the transfer of funds to a merchant's bank account. The revenue raised as a variable charge per transaction purely on account of financial

[3] A summary of existing literature at the point is provided by Evans and Schmalensee (2005a)

[4] In practice, this role is performed by different types of firms. It includes the *acquirer proper* or *gateway* who provides POS terminals for traditional cards and secure platforms in e-commerce, a *payment processor* who handles the routing of payments from issuer to merchant and *payment facilitators* who enable easier access to gateway services, especially to small merchants.

intermediation (excluding, for example, charges associated with leverage provided to consumers by a bank issuing a credit card) is referred to as the *merchant discount rate* (MDR), since it is usually exacted directly from merchants, and is expressed as a percentage value of transaction price (plus a fixed fee if applicable, as is the case with debit cards in the United States).

In the case of so called *closed loop* or three-party networks, such as the aforementioned examples of American Express and Discover, the issuer and acquirer are a single entity and no other significant charges are incurred on a per transaction basis. However, the biggest payment card networks, VISA and MasterCard, are *open loop* systems where the network operator licenses multiple banks to function as either issuers or acquirers (or both). Since their inception, these networks have incorporated a centrally determined *interchange fee* as a tool for sharing MDR revenues among the two parties, and is paid by the acquirer to the issuer involved in a given transaction. This fee is simply voted for by the members participating in a given open loop network, with voting shares proportional to transaction volume [5]. Since these networks feature multiple banks and the acquiring end of the market is regarded to be very competitive[6], some authors refer interchangeably to the MDR and the interchange fee, although perfect pass-through does not necessarily occur in all markets under evaluation. Both parties may additionally charge fixed fees to access the network: in the case of acquirers, this involves the maintenance of the merchant's bank account together with the rental of the POS terminal used to swipe payment cards; issuers charge consumers for newly minted cards, account maintenance and renewal.

[5] Evans and Schmalensee (2005b) discusses the evolution of Visa and MasterCard's governance since their inception as four-party networks in the 1970's. Some significant changes will be mentioned in the Model section of the article.

[6] Rochet and Tirole (2002) is an example of several models that assume merchant acquisition to be a perfectly competitive activity, while Carbo Valverde et al. (2016) reports a correlation of .94 between interchange fees and the MDR in a panel data of Spanish banks participating in the two major payment card networks over the course of a decade.

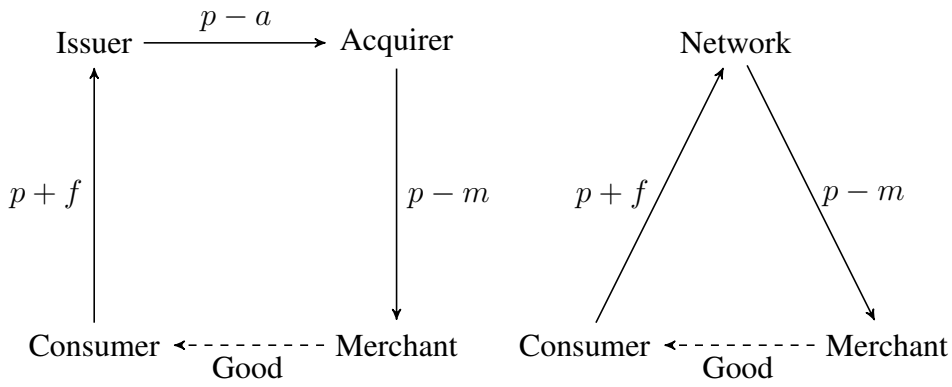


Figure 1.1: Sequence of payments in a four-party payment card network (left) and a three-party network (right). p is the transaction price of the good, a is the interchange fee and m is the merchant discount rate. f are any payments made by customers to banks on a per-transaction basis, or rewards if said value is negative (as is usually the case).

Lastly, *general purpose* (as opposed to store-based) payment cards may differ slightly in their function. The types most commonly seen are *credit cards*, which facilitate revolving credit to customers; *debit cards*, which draw funds immediately from a customer's checking account through one of different payment networks (signature debit cards operate through the same networks as credit cards do, while PIN cards operate through the same networks as ATMs and share their authentication protocol); *charge cards* work like credit cards, but balances must be paid in full at the end of every month.

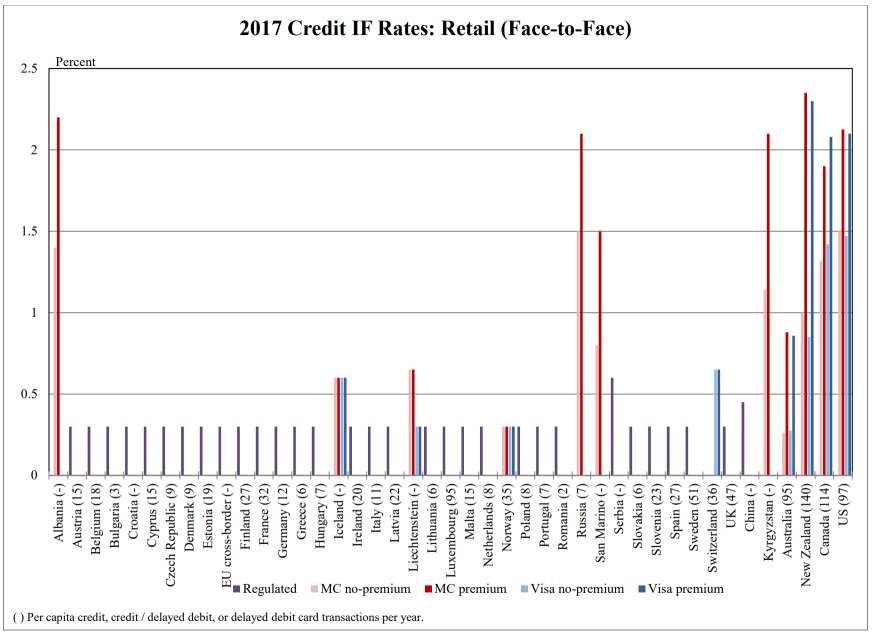


Figure 1.2: Cross-country variation in interchange fees for retail transactions of featured open loop credit card networks. Source: Kansas City Federal Reserve (2017)

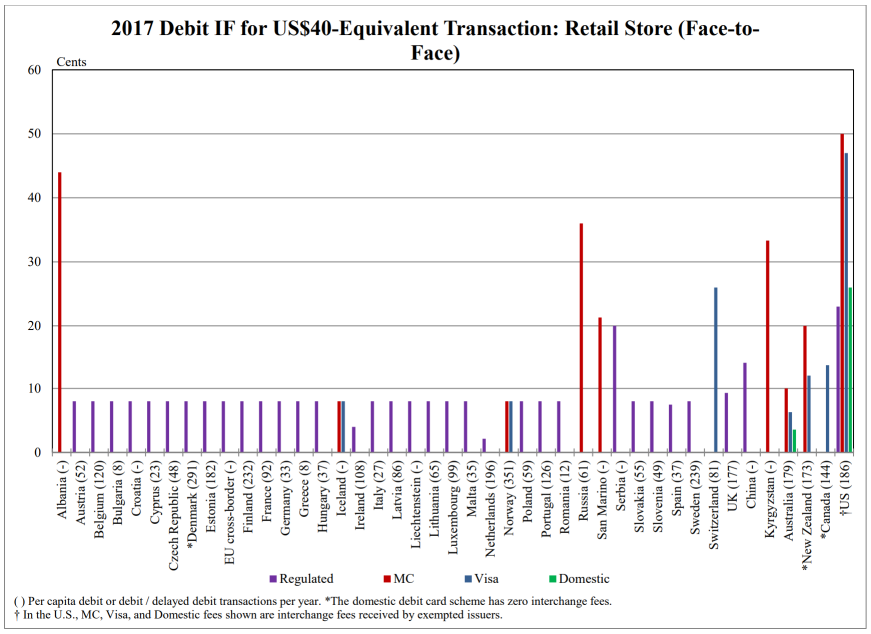


Figure 1.3: Cross-country variation in interchange fees of featured open loop debit card networks. Issuers exempt from US regulation are banks with less than USD 10 billion in assets. Source: Kansas City Federal Reserve (2017)

1.1.2 Payment card markets and regulation in Argentina

At the beginning of 2016, payment card markets in Argentina exhibited some noticeable differences from other cases around the world, mostly involving the acquisition end of the platform[7]. VISA, the largest network in the country with over 60% market share by transaction volume, effectively operated like a closed loop system since a consortium of 14 private and public banks owned a firm, PRISMA, with an exclusive license to perform acquisition and payment processing services for VISA together with the maintenance of one of two ATM/ETF networks in the country. All networks are allowed to vary the MDR they charge down to the retail sector involved in a transaction, but until early 2017 most sectors were charged a statutory limit of 3% for credit cards and 1.5% for debit established in 1995. Interchange fees ranged from 2.7% to 2.9% depending on the network involved[8].

The regulators involved with this and closely related markets are the aforementioned antitrust agency (CNDC) and the local central bank (BCRA). The latter has introduced sweeping reforms throughout the financial services industry with the objective of promoting their use and thus reducing the presence of the informal economy in Argentina[9]. Some of the most relevant measures for this study include a mandate for all banks to offer, free of charge, debit cards and "savings accounts" (which in practice function as interest-bearing checking accounts, since they can serve as sources of funds for most electronic transfers) for all residents in Argentina, and the introduction of a new clearinghouse that provides immediate transfer of funds (as opposed to traditional systems that could delay transfers until the closing of the day, or 48 hours) through novel payment systems operated by the private sector, that are accessed through mobile POS

[7] A report by the local antitrust authority, CNDC (2016), currently in the public domain at `https://www.argentina.gob.ar/sites/default/files/cndc_resol_invmerc_tarjetas_2.pdf`, provides the lay of the land together with some descriptive statistics and a brief comparison with similar environments throughout the world.

[8] These include VISA and MasterCard, who together command over 80% of transactions by volume. Other networks include American Express and local closed loop networks Tarjeta Naranja and Nativa

[9] A more comprehensive list of reforms is provided by the central bank at `http://www.bcra.gob.ar/Institucional/Medidas_adoptadas.asp`

terminals, P2P transfers (with users identified by debit card or bank account), and e-commerce gateways. Moreover, merchants with yearly revenues beyond a particular threshold must forcibly accept all debit cards as payment.

In its analysis of VISA's local operation, CNDC and local retail representatives also recommended antitrust policies with some precedent around the world. Chief among them is the progressive introduction of a cap on debit and credit card interchange fees for all networks, with the following schedule:

Date	Debit IF	Credit IF
04/2017	1.0%	2.0%
01/2018	0.9%	1.85%
01/2019	0.8%	1.65%
01/2020	0.7%	1.5%
01/2021	0.6%	1.3%

The other aspect of regulation involves vertical integration in VISA's operation. During September 2017, the shareholders of PRISMA agreed to divest themselves of the company with provisions that will discourage future vertical integration, including restrictions on local network operators from purchasing firm shares, forcing PRISMA to extend some of its processing services to other networks and discontinuing others, such as giving the option to merchants of receiving advance payment 48 hours after transaction, in order to encourage entry by other participants.

On an aggregate level, transactions by payment card are deeply rooted in Argentina's retail market. Salas and Demo (2017) documented that domestic retail sales amounted to roughly 62 billion USD in 2015, of which 45% was paid for with credit cards, 25% with debit and the remainder with cash. Debit cards constitute 54% of general purpose payment card issue, with the remainder composed of credit cards. Among the latter, 64% are issued by financial entities (essentially banks) who account for nearly 75% of total issue; other issuers include nonfinancial companies, who usu-

ally concentrate their operation within a single region (some of these are subsidiaries owned by parent banks, and are differentiated in some key characteristics such as lower fees and rewards). Roughly half of all credit card transactions are paid in a single installment, and the stock of credit card debt amounts to 20% of all banks' assets. The variable fees paid to payment intermediaries that will be analyzed in this paper totalled about 1 billion USD in 2015, mostly composed of the 3% maximum merchant discount rate for credit card transactions mentioned above.

1.2 Literature Review

1.2.1 Theoretical analysis

Several works summarize the current state of research on payment cards at the moment of publication. Rysman and Wright (2014) takes stock of the existing theoretical literature, with a particular focus on models of payment systems as *platform* or *two-sided* markets with consumers and merchants respectively. This body of work stresses the existence of different types of network externalities, which refers to the role adoption rates by each side of the market play in the demand from both of them for intermediation. Models differ mainly in the set of assumptions they adopt and the phenomena they are able to accommodate: starting from an environment where a monopolist offers one payment system with a single outside option for merchants and consumers, some papers like Rochet and Tirole (2002) incorporate *merchant internalization*, that is to say that merchants consider the strategic effects that card acceptance induces when competing with other suppliers; Bedre-Defolie and Calvano (2013) allow for two-part cardholder pricing, which consists of a fixed usage or access fee and a variable charge and highlights the asymmetry between consumers, who ultimately decide whether a transaction will be realized with a payment card or not, and merchants whose decision is limited to accepting those payments (or not); Guthrie and Wright (2007) incorporates multiple platforms and shows the role *multihoming* - the adoption of multiple platforms by a given user, be it consumer or merchant - plays in determining how competition between systems affects equilibrium interchange fees. A key factor distinguishing these

models from other work on two-sided markets is the fact that the platforms under consideration are operated by multiple parties, so that internalization of forces across both sides of the market (an elementary example of which is provided in Rochet and Tirole (2003) for a monopolistic, fully integrated platform) does not occur automatically, and is enabled by the introduction of interchange fees.

1.2.2 Analysis of previous regulation

While some empirical models have tried to directly address some of the concerns raised by the previously mentioned theoretical models, many others have focused on the effects of interchange fee variation on the various parties a payment network caters to. The article with the most comprehensive data available is probably Carbo Valverde et al. (2016), which tracks a rich panel of 45 Spanish banks from 1997 through 2007. With a system of equations for consumer and merchant adoption on the extensive (card penetration) and intensive margins (transaction volume), they document the existence of network externalities as measured by a positive coefficient of merchant adoption on consumer demand for payment cards (and viceversa), as well as a negative effect of interchange fee raises on merchant acquisition.

Other analyses draw directly from interchange fee regulation policies. Chang et al. (2005) follows the case of Australia, which similarly to Argentina placed a cap on credit card interchange fees that effectively halved their level to 0.55% of transaction value. The express purpose of the Reserve Bank of Australia was to lower credit card issue but, although roughly 40% of the reduction in issuers' income was passed onto fixed card usage fees for consumers, adoption was not significantly affected and the corresponding reduction in merchant discount rates was not passed through to consumer prices. Manuszak and Wozniak (2017) studies the introduction of Regulation II of the Dodd-Frank Act in the United States, which starting in 2011 restricted debit card fees to half their effective level but only for banks with over USD 10 billion in assets. They document the

availability of free checking accounts in terms of minimum balances required and the fees attached to accounts that were not. The main finding of the article is that, although banks covered by the regulation passed the interchange fee reduction on to higher consumer fees as suggested by theory and similar past examples, so did exempt banks increase these usage charges, even though several of them kept interchange rates above the cap.

1.3 Data

1.3.1 Description

The data available for analysis consists of a bank-level panel of financial entity[10] characteristics and consumer charges for a host of payment cards and related services (such as deposit account maintenance costs and charges associated to mortgages, secured loans and personal credit). All data is currently provided by the Central Bank of Argentina, with bank characteristics published monthly in the *Blue Book*[11] and usage charges published through a provision of the Transparency Regime for consumer products[12].

The observed consumer charges consist of fixed access fees, which are the sum of a monthly maintenance fee and an annual renewal fee[13], as well as interest rates on outstanding balances. They are reported on a bank and tier-level basis, according to a classification of five credit card types: national cards, which can only be used in domestic transactions, international cards, and three categories of premium cards, which usually command higher maintenance fees but also offer greater rewards per transaction, as well as a larger credit line. However, there is no distinction

[10]Notably, this excludes some credit cards who are not financial entities and thus outside the oversight of the Central Bank's Transparency Regime

[11]Online at `http://www.bcra.gob.ar/SistemasFinancierosYdePagos/Sistema_financiero.asp?opcion=1&tit=1`

[12]Data for the current month is publicly available at `http://www.bcra.gob.ar/BCRAyVos/Comisiones_cargos.asp`

[13]It is worth noting that this fee, while relatively high (the sample average is 75 USD when converted with end-of-period exchange rate), is commonly waived by consumers. Conditions for doing so include tying wage deposits to a checking account associated with a credit card, or maintaining a balance beyond a threshold in said account.

made between the multiple networks that a bank may operate with, and thus only one item is reported per category in each observation. The panel spans observations of 52 banks from October 2016 to September 2017. Summary statistics of the data are described below, with all values reported in nominal local currency units (for reference, the exchange rate varied from 15.12 to 16.97 ARS/USD in this time frame).

Table 1.1: Consumer charges for national cards

Statistic	N	Mean	St. Dev.	Min	Max
Total access fee	516	1,288.589	406.911	348.480	2,479.430
Renewal (yearly)	516	487.965	288.082	0.000	1,363.670
Maintenance (monthly)	516	66.719	17.132	19.360	126.460
Interest rate	511	67.560%	21.984	36.880	153.690

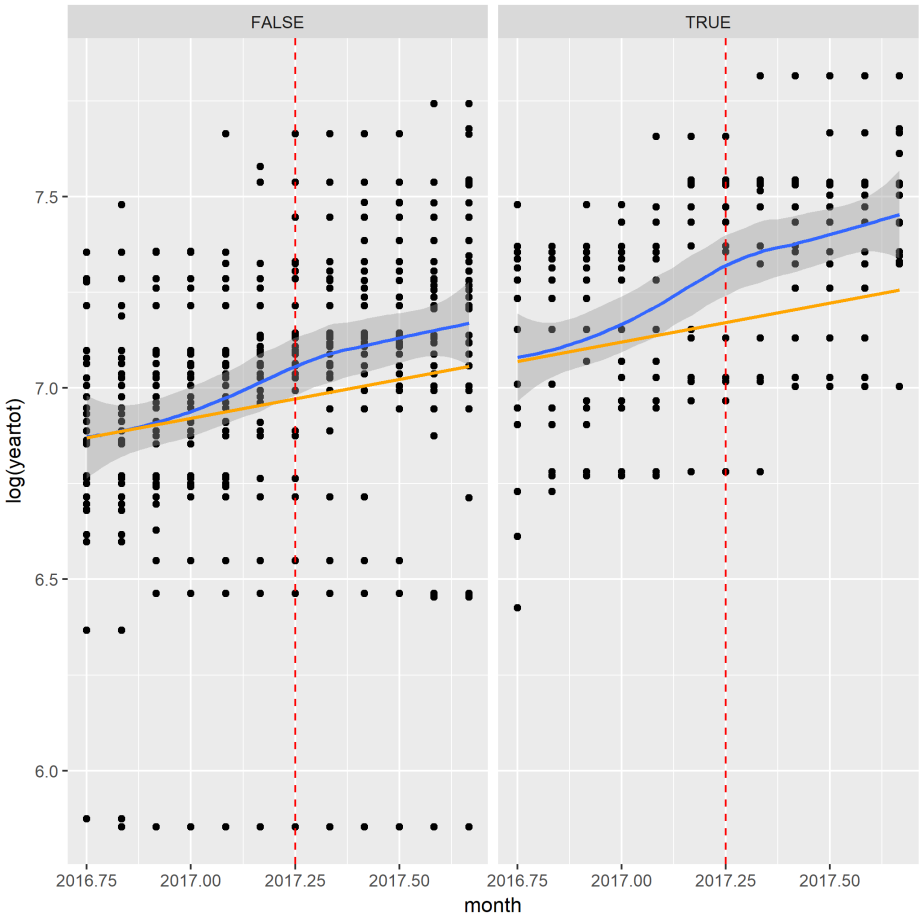


Figure 1.4: Scatter plot of total yearly fees charged by each bank in the sample for each month observed in the data. Observations are split into those of banks with equity in PRISMA, displayed on the right panel, and banks who are not integrated in the left panel. The dashed vertical red line indicates the first stage of the programmed decrease in interchange fees, dated April 2017. The blue line is a local linear regression of fees with a time trend component, and the orange line displays CPI inflation during the same time period (with the same intercept as the blue line). CPI inflation averages to 20.3% in this time period, while a linear regression of log fees with dummies for regulatory intervention and PRISMA ownership yields a time trend of 37.7%. Output of this simple regression is reported in table 3.7 in the appendix.

The bank characteristics include detailed balance sheets with over a thousand items reported on a monthly basis, as well as additional variables reported on a quarterly basis. The balance sheet items include the stock of credit card debt, as well as other assets held by banks against the private sector and consumer deposits. Some key variables among the additional characteristics include the stock of credit and debit cards issued by each bank, as well as the count of uniquely identified

credit card holders. The entities covered in both panels are the same as in the fee dataset described above; however, the time period stretches only until June 2017.

Table 1.2: Balance sheet summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Assets (in ARS millions)					
Mortgages	139	1,486,445	3,071,465	8	15,767,150
Overdrafts	340	2,044,697	3,048,500	3,323	11,941,148
Signature credit lines	300	3,148,967	5,279,595	101	22,668,647
Personal loans	385	5,203,692	7,132,541	25,073	40,193,483
Credit card debt	385	5,308,736	8,791,125	5,746	43,483,205
Liabilities (in ARS millions)					
Checking accounts	335	6,285,971	10,005,637	67,387,924	9,709
Savings accounts	358	3,831,127	9,518,063	1,588	64,211,680

Table 1.3: Additional variables, summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
Credit cardholders	169	527,974	754,784	430	3,669,772
Credit card issue	168	826,453	1,405,410	1,259	7,148,170
Debit card issue	155	1,001,001	1,447,299	0	7,404,933

The next figure depicts systematic differences in the consumer base between PRISMA owners and non-integrated issuers. On average, the former enjoy a much larger presence in the market:

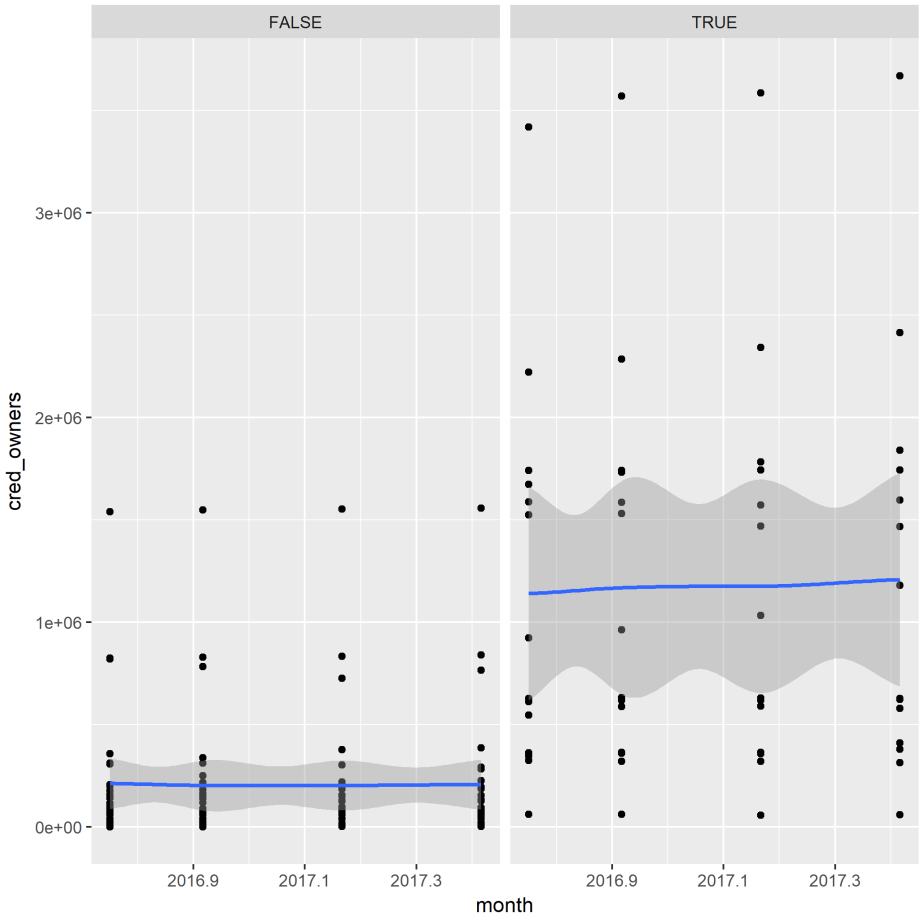


Figure 1.5: Scatter plot of credit card issue across banks in the sample period. The right panel includes banks with equity in PRISMA; the left panel includes the remainder.

1.3.2 Exploratory analysis

Tables 3.5 and 3.6 included in the appendix report some bare empirical analysis of the available data. Since the observed data distinguishes between banks rather than the complete menu of cards, I formulated a model of consumers faced with the discrete choice of a *bank* to intermediate in all transactions by payment card. Since payment cards often come bundled with other financial services, a selection of balance sheet items was included as a vector of characteristics x_i (including credit card debt) in the equation specified below for each i of n banks in the sample:

$$\log(s_i) - \log(s_0) = \alpha F_i + x_i'\beta + \xi_i \tag{1.1}$$

s_i is the market share of bank i in the market of credit card holders (or issued credit cards, in an alternate specification on panel 2 in table 3.5). s_0 is the share of the outside option, defined as the remainder of subtracting total credit card issue from the amount of debit cards existing in the market: I propose this as a measure of market size since as of April 2016 banks are mandated to offer a savings account bundled with a debit card free of charge to any consumer who would require one. Therefore, this should be an adequate indicator of the sum total of bancarized individuals in the economy (the main issue is that the resulting market may be *too large*, as consumers can hold more than one debit card and unique debit card holders are not identified in this data set). F_i is the yearly total access fee charged by bank i. Month fixed effects were included for this estimation.

Table (3.6) includes the estimates of this 'demand' equation with instruments for F_i and the stock of credit card issue, the two most obviously endogenous variables in the equation above. The instruments were drawn from the usual set of BLP instruments as described by Nevo (2000), although a supply equation was not included in this estimation. The next section borrows from the theoretical literature to suggest a set of equations that satisfactorily accounts for banks' pricing decisions, as well as the variables that I would need to observe in order to conduct a complete estimation.

1.4 Model

1.4.1 Setup

The model used for extending the previous analysis is a variation of Bedre-Defolie and Calvano (2013). It includes the decision of a measure 1 of consumers choosing whether or not to purchase

a payment card from a particular issuer within a single network and the allocation of consumption amongst the available payment instruments, the decision of a measure 1 of merchants choosing whether or not to accept card payments from a network, and the choice of some fees (the ones that are bank-specific) by members of the payment card network, according to their role. These banks may belong to a three or four-party network; in the latter, they may specialize in issuing or provide issuing and acquisition service simultaneously.

The surplus derived purely from the consumption of a single good consists of an exogenous monetary value v, while monopolistic merchants choose a single list price p to be charged to all consumers, regardless of the payment method employed (this is referred to as *price coherence* or *no surcharging* in the literature). In addition to consumption surplus, a patron also has a net benefit b_B from using a payment card in a given transaction, drawn from a distribution $G(b_B)$ satisfying the increasing hazard rate property. The merchant similarly enjoys a benefit b_S from accepting a card payment which is drawn from a distribution $K(b_S)$ satisfying the same assumptions. Consumption surplus v is assumed to be sufficiently high that the merchant does not wish to screen consumers based on their preference for card usage, which is a particular form of *merchant internalization* analyzed by Guthrie and Wright (2007) among others[14].

When considering the choice of a bank for payment intermediation, both merchants and consumers have a fixed surplus of B_S and B_B respectively derived from subscribing to a bank's services. Acquisition services are assumed to be homogeneous so B_S consists of a scalar-valued random variable even when multiple banks offer services to merchants. However, banks' issuing services are assumed to be heterogeneous, with a joint distribution over the membership surplus from each of n banks $B_B = (B_{B,1}, ...B_{B,n})$. Assumptions on this distribution are discussed when

[14]If there exist lower bounds for b_B,b_S, this assumption can be stated as

$$v \geq c - \underline{b_B} - \underline{b_S} + \frac{1 - G(\underline{b_B})}{g(\underline{b_B})}$$

computing the demand function for card adoption.

Finally, banks have a cost of performing issuing and acquisition services on a per transaction basis of c_I and c_A respectively. An acquirer perceives gross income of $m - a$, where m is the merchant discount rate and a is the interchange fee. Issuers' gross income consists of $f + a$, where f is the per transaction usage fee (or reward, if it assumes a negative value) paid by consumers who use a card. Subscription or access fees for consumers and merchants are respectively F_i and M.

Strategic interaction between players and their information processes unfold according to the following timeline:

$t = 0$ Network-wide m,M and a are predetermined. They could be mandated by the owners of the central network[15], a regulator, or result from bargaining between consumers, merchants and intermediaries.

$t = 1$ After observing m and a, a fixed stock of n banks chooses its fee structure, consisting of (f_i, F_i) for the consumer side.

$t = 2$ Consumers and merchants realize their subscription benefits B_B, B_S and choose up to one bank to patronize, if any.

$t = 3$ Merchants set retail prices. Consumers and merchants realize per transaction benefits b_B, b_S and *consumers decide whether to purchase a single good or not*. Once they have decided to purchase a good, they decide to do so with cash or card.

[15]The incentives of network owners such as VISA and MasterCard have historically varied widely. In the case of VISA, it operated as a non-profit franchise until 2003, with member banks holding ownership stakes in the company; they also voted (with shares proportional to ownership) on the components of fee structure common to the entire network, the bulk of which is the interchange fee. Fees paid directly to the network by member banks included a fixed subscription fee and an assessment fee. Since then, VISA became a publicly-traded company, with member banks relinquishing control over *some* of its operations, such as Canada and the U.S.. Notably, European operations continued under the oversight and collective governance of relevant member banks. This is mentioned in Bedre-Defolie and Calvano, with a more extensive discussion provided by Evans and Schmalensee (2005b)

Heterogeneity in b_B serves the role of introducing a margin for usage-based fees and rewards to affect payment card transaction volume, and the timing of the information flow makes it so that consumers are homogeneous in terms of usage surplus: the services offered by different banks will be valued differently based purely on B_B.

1.4.2 Equilibrium

A subgame-perfect Nash equilibrium of this game consists of a price level for merchants p, a fee structure for each participating bank $\{(f_i, F_i)\}_{i=1}^n$, the merchant acceptance rate D_S of card payments, shares in the card membership market $Q = \{Q_i\}_{i=1}^n$ and the share of card owners from a given bank who prefer to pay by card when possible, $D_B = \{D_{B,i}\}_{i=1}^n$. To map D_B to a more readily observable variable, D_B and D_S are aggregated through a matching function to produce the total number of transactions by payment cards, $\mathcal{M}(D_B, D_S)$. In the original model, $\mathcal{M}(D_B, D_S) = D_B D_S$, so as to represent the probability of randomly (and independently drawn) drawing a consumer and merchant such that the former wanting to pay by card and the latter willing to accept such a payment.

Given the assumptions on consumption surplus v, merchants will price their good at p and the entire market will be supplied. Therefore, any fluctuation in payment card transaction volume will happen independently of fixed aggregate consumption. Rysman and Wright (2014) discusses a range of models where interaction between card and total transaction volume is accounted for as part of a broader analysis of merchant internalization.

When it comes to payment card transactions, merchants only choose on the 'extensive' margin of whether to accept card payments from any and all consumers willing to use it. They will do so when the static benefits of doing so are positive:

$$D_B(b_S - m) + B_S \geq 0 \tag{1.2}$$

This is a simple computation based on the average surplus from each transaction and reflects a fundamental asymmetry between merchants and consumers in the model, since the latter make the 'intensive' decision to pay by card or not single-handedly. The authors of the original model argue that this decision rule accommodates a normalization without loss of generality of $B_S = 0$, such that the above rule condenses to a merchant accepting card payments when $b_S > m$[16] and the merchant acceptance rate can be computed as:

$$D_S(m) = Pr(b_S > m) = 1 - K(m) \tag{1.3}$$

The decision of a consumer who has subscribed to card services is also simple. Given that banks are homogeneous in the surplus they provide consumers on a per transaction basis (other than the usage-based fees/rewards f_i), all the heterogeneity across cardholders from different banks reduces to the thresholds for card usage:

$$D_B(f_i) = Pr(b_B > f_i) = 1 - G(f_i) \tag{1.4}$$

Since cardholders make a prior decision of acquiring a card, it is necessary to compute their surplus from the transaction stage, represented as ex ante expected surplus per transaction mul-

[16]I will also adopt that normalization, given that I lack data on merchant acceptance and its drivers in Argentina for the relevant time period. The European The European Commission (2015) has strived to assess the level of cost savings from accepting card payments in order to design cost-based benchmarks for interchange and other fees. The cited report includes survey-based and econometric inference on fixed and variable cost savings, with long-run estimates of total cost savings ranging from 0.2 to 0.4% of transaction price, including fraud prevention and labor savings in front and back-office payment processing.

tiplied by transaction volume $\mathcal{M}(D_B, D_S)$. Bedre-Defolie and Calvano refer to this value as the *option value of card ownership*:

$$\phi_B(f_i, m) = E[b_B - f_i | b_B \geq f_i] D_B(f_i) D_S(m) \tag{1.5}$$

In the preceding period, consumers choose up to one card from the menu of existing banks to hold. They will choose the bank that maximizes their net payoff: $B_{B,i} + \phi_B(f_i, m) - F_i$. The resulting membership shares $Q = \{Q_i\}_{i=1}^n$ thus depend on *net* fees: $t_i = F_i - \phi_B(f_i, m)$. For the purposes of this model, market shares Q_i are assumed to be decreasing in a bank's own net subscription fee, increasing in others', and a jointly log-concave function. These assumptions will be shown to be compatible with the functional form assumptions used for identifying the model in the next section.

The last decision to model consists of a bank's choice of fee structure. Given that most banks in the sample function within a four-party network structure, their objective function will be discussed in more detail. Consider first a bank who is not integrated and thus offers issuing services exclusively: its revenue stems purely from fixed and variable income from the cards customers have purchased. The fixed margin is the access fee F_i; profits accrued on a per-transaction basis is the sum of revenue f_i net of costs $c_I - a$, and transaction count *per cardholder* is $D_B(f_i)D_S(m)$. The bank's problem is thus:

$$\max_{F_i, f_i} [(f_i + a - c_I) D_B(f_i) D_S(m) + F_i] Q_i(F_i - \Phi_B(f_i, m), F_{-i} - \Phi_B(f_{-i}, m)) \tag{1.6}$$

Bedre-Defolie and Calvano show that the solution to this problem consists of marginal cost pricing on the variable margin, and a Lerner rule on its residual card subscription demand:

$$f_i(m,a) = c_I - a$$
$$F_i(m,a) = -Q_i(F_i - \Phi_B(f_i,m), F_{-i} - \Phi_B(f_{-i},m)) \left(\frac{\partial Q_i(F_i - \Phi_B(.), F_{-i} - \Phi_B(.))}{\partial F_i} \right)^{-1}$$

The intuition behind this result is straightforward. If variable fees exceed the issuing cost per transaction, they could be lowered on the margin so that the entire surplus on that margin is captured through an increase in F_i with card membership being kept constant. A similar result holds for integrated issuers, who additionally perceive revenues from merchant acquisition. This profit consists of the acquiring margin on each transaction $m - c_A - a$, scaled by the membership share of all banks j, Q_j, and the transaction count for each issuer $D_B(f_j)D_S(m)$. The objective function resolves to:

$$\max_{F_i, f_i} [(f_i + a - c_I) D_B(f_i) D_S(m) + F_i] Q_i(.,.) + (m - c_A - a) \sum_{j=1}^{n} D_B(f_i) D_S(m) Q_j(.,.) \quad (1.7)$$

It is shown in the appendix that the pricing rule for variable fees still consists of perfect pass-through. However, the per-transaction margin now consists of the issuing margin plus the acquiring margin: $m - c_A + c_I$. Notably, since the interchange fee represents pure revenue for the issuer and loss for the acquirer, it disappears from this expression. The first-order condition for fixed fees is also reported, which now balances the effect of changes in F_i on the bank's own issuing revenue with the effect on other banks, given that i perceives the acquiring margin on all transactions performed through the card network:

$$f_i(m,a) = c_A + c_I - m$$
$$0 = Q_i(.,.) + F_i \frac{\partial Q_i(.,.)}{\partial F_i} + \sum_{j \neq i} (m - c_A - a) D_B(f_i) D_S(m) \frac{\partial Q_j(.,.)}{\partial F_i}$$

The first-order conditions for all banks' fixed fees F can be stacked up and represented in a matrix form reminiscent of conventional Nash-in-prices supply models:

$$\mathbf{q}(\mathbf{F}, \mathbf{f}, m) + \Omega . D_F(\mathbf{F}, \mathbf{f}, m) = 0 \tag{1.8}$$

Where $D_F(.)$ is the Jacobian matrix of card membership demand and Ω is an ownership matrix, whose coordinate ij indicates whether the bank i in a given row internalizes the effect on bank j's demand, and to what degree. Since some banks *partially* own other banks' transactions, this matrix assumes the expression below. Let ι be an n-dimensional dummy vector that indicates whether a bank is integrated or not:

$$\Omega = \text{diag}(F_1, ..., F_n) + \iota\Gamma(\mathbf{f}, m))$$

$$\Gamma_{ik}(f_k, m)) = (m - c_A - a) D_B(f_k) D_S(m)$$

$$f_k = \begin{cases} c_I - a & \text{if } \iota_k = 0 \\ c_A + c_I - m & \text{if } \iota_k = 1 \end{cases}$$

1.4.3 Identification

This model is identified through four moments analogous to others employed in the empirical literature, such as Carbo Valverde et al. (2016), together with some functional form assumptions. In particular, I will look at the merchant adoption rate D_S, the intensity of payment card usage by consumers who have become cardholders D_B, market shares in the card subscription market Q_i, and all of n issuing banks' first-order conditions for access fees, depending on their type. The equilibrium characterization of these variables is summarized below:

$$
\begin{aligned}
D_S(m) &= Pr(b_S \geq m) = 1 - K(m) \\
D_B(f_i) &= Pr(b_B \geq f) = 1 - G(f_i) && \forall i \\
Q_i(F_i - \Phi_B(f_i, m), F_{-i} - \Phi_B(f_{-i}, m)) &= Pr(i \in \arg\max_j U_j(F_j, f_j)) && \forall i \\
\mathbf{q}(\mathbf{F}, \mathbf{f}, m) + \Omega . D_F \mathbf{q}(\mathbf{F}, \mathbf{f}, m) &= 0
\end{aligned}
$$

One of the more readily accessible functional forms for discrete choice problems is that of a multinomial logit, which results from each of b_S, b_B and $\{b_{B,i}\}$ being distributed as (independent) extreme value type I random variables, centered respectively on $\delta_S, \delta_b, \delta_{B,i}$. This functional form is compatible with the previous assumptions of increasing hazard rates and gives a closed form expression for three relevant variables: the function mapping fees to market shares in transaction and card membership markets, the gradient of said function and the option value of card usage, ϕ_B, as the difference between the expected value of the maximum of two EV random variables (centered on δ_b and 0), and a single one representing the outside option of paying with cash, whenever a consumer matches with a merchant who accepts card payments:

$$
\begin{aligned}
D_S(m) &= Pr(b_S \geq m) = \frac{e^{\delta_S - m}}{1 + e^{\delta_S - m}} \\
D_B(f_i) &= Pr(b_B \geq f) = \frac{e^{\delta_b - f}}{1 + e^{\delta_i - m}} && \forall i \\
Q_i(F_i - \Phi_B(f_i, m), F_{-i} - \Phi_B(f_{-i}, m)) &= \frac{e^{\delta_{Bi} - F_i + \phi_B(f_i, m)}}{1 + \sum_{j=1}^{N} e^{\delta_{Bj} - F_j + \phi_B(f_j, m)}} && \forall i \\
\mathbf{q}(\mathbf{F}, \mathbf{f}, m) + \Omega . \nabla_F \mathbf{q}(\mathbf{F}, \mathbf{f}, m) &= 0 \\
\phi_B(f_i, m) &= D_s(m) \log\left(1 + e^{\delta_b - f_i}\right) \\
f_i &= \begin{cases} c_I - a & \text{if } \iota_i = 0 \\ c_A + c_I - m & \text{if } \iota_i = 1 \end{cases}
\end{aligned}
$$

This model will be used for the simulations reported below; in addition, this system highlights the necessary variables for a complete estimation of the model: cardholding shares, together with access fees, transaction volume and merchant adoption rates, allows for a recovery of $\delta_S, \delta_b, \{\delta_B\}_{i=1}^n, c_A$ and c_I if instruments are available. An immediate example of these instruments, mentioned in section 1.3.2, includes the standard set of BLP variables derived from product (or in this case, bank) characteristics.

1.5 Results

1.5.1 Simulation

The figures below depict some comparative statics of equilibria in the market of payment card issue when the interchange fee is shifted exogenously. The fundamental specification of this simulation consists of five homogeneous firms (that is, with the same values for δ_b and δ_B), from which three different benchmarks are drawn[17]. In the first one, named **homogeneous firms**, none of the five issuers offer acquisition services and the merchant discount rate m is priced to marginal cost of acquisition: $m = c_A + a$. In the two remaining benchmarks, two of the issuers are now integrated with the acquisition leg of the network and split equally the profits raised from this end. The first of these two benchmarks, **perfect pass-through**, keeps the acquiring margin constant since m is lowered in the same proportion as a (however, a strictly positive margin ε is added in order for integrated issuers to behave differently from nonintegrated ones) as it goes down. The final benchmark, **no pass-through**, keeps the merchant discount rate constant as the interchange fee goes down. Therefore, the acquisition margin from other banks *increases* for issuers at the same time that the margin on banks' own transaction remains constant (as the change in interchange fees merely reflect a payment 'from the bank to itself', and thus own margins $f + m - c$ are unchanged). The reason for the inclusion of these two benchmarks is that when

[17]Parameter setup is as follows: $\delta_{B,i} = 1.5 \ \ \forall i, \delta_S = 0.03, \delta_b = -0.01, c_A = 0.001, c_I = 0.01$. Lastly, I add a parameter N that represents the volume of transactions per customer (so that the measure of customers sums to N instead of 1) I worked with a value for N of 100 for this simulation.

interchange fees dropped from a variable starting point of $2.7 - 2.9\%$ to 2% in April 2017 several market participants, including PRISMA shareholders and associations grouping merchants and other credit card issuers, collectively negotiated the reduction of the MDR from 3% to 2.5%, a case of incomplete pass-through that falls between the two extremes described above. Since the model described above does not account for an endogenous determination of the MDR, both cases are mentioned.

These comparative statics depend chiefly on the functional form assumption of logit demand and elasticities, as well as broader economic trade-offs in play.

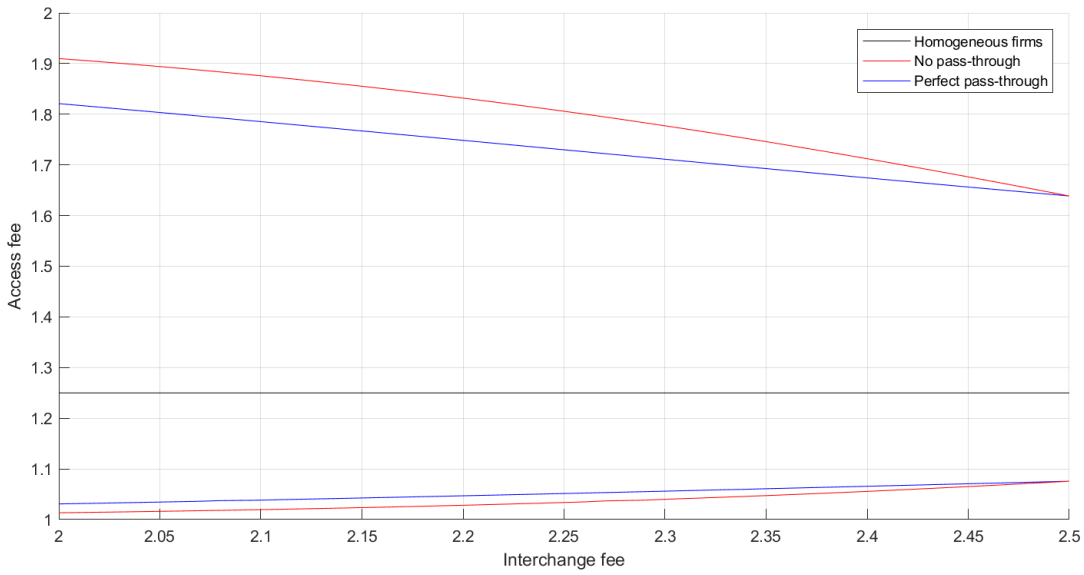


Figure 1.6: Comparative statics of access fees F_i for a varying range of interchange fees a. The colored lines *above* the black line represent the fee structure of *integrated* issuers, while the ones below correspond to the non-integrated firms.

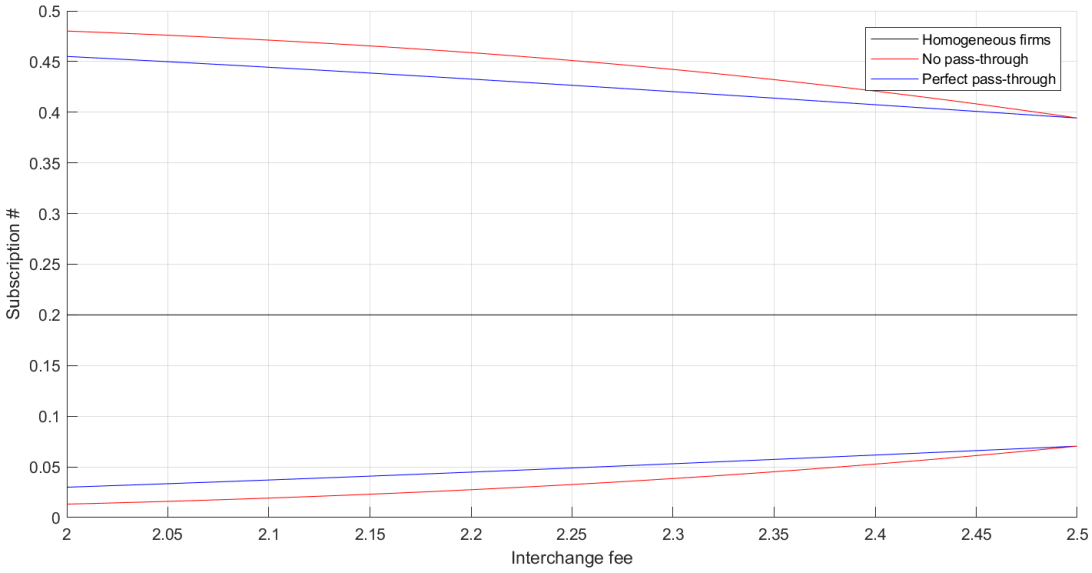


Figure 1.7: Comparative statics of cardholder market shares Q_i for a varying range of interchange fees a. As before, it is the integrated banks who have more subscribers than the homogeneous firms benchmark.

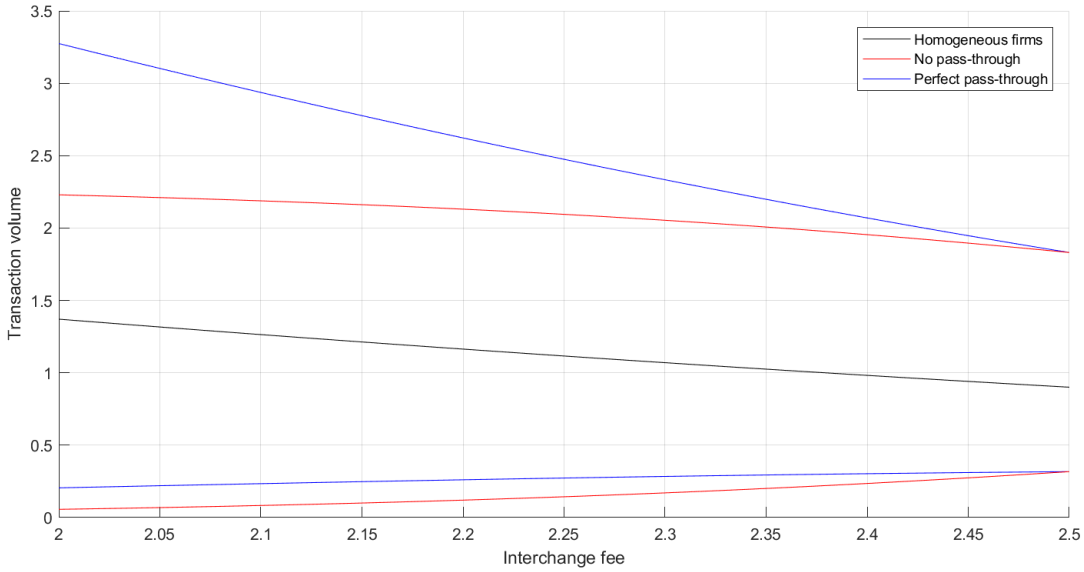


Figure 1.8: Comparative statics of transaction volume by payment card: $Q_i(.)D_S(m)D_b(f_i)$ for a varying range of interchange fees a. As before, it is the integrated banks who command more transactions than the homogeneous firms benchmark.

The parameters were chosen so that transaction volume and cardholders' transaction surplus increase as the interchange fee goes down in the homogeneous firms benchmark: this can happen because along the locus of fees where costs are perfectly passed through to price (in this benchmark, $m + f = (c_A + a) + (c_I - a)$, a trade-off occurs when a is reduced: consumers receive less money on each transaction as rewards are curtailed, but more merchants accept cards as the reduction in the interchange fee is passed through to the merchant discount rate. However, access fees and cardholding volume are constant as a and m diminish in tandem. This need not always be the case, and is a consequence of the logit specification for transaction demand as well as *every consumer choosing a card* for the parameters supplied. F_i own-elasticity of cardholding demand in this model is:

$$\frac{\partial Q_i}{\partial F_i}\frac{F_i}{Q_i} = -F_i(1 - Q_i)$$

Even though the transaction volume and ϕ increase as a decreases, the shock is common to all banks. Therefore, since nobody opts away from holding a card at all, then market shares are invariant in the shift of the interchange fee/MDR and the optimal F_i is constant too.

The above argument breaks down with integrated firms since the gain in transaction surplus is asymmetrically distributed across the market: since integrated firms own a wider margin of each transaction, they have more money to throw back at consumers despite the intrinsic value of holding any card and using it for any transaction being equal. In both benchmarks with partial vertical integration, the integrated firms use this to their advantage and mark up their prices: notably, it is in the no pass-through benchmark, where margins on an integrated issuer's own transactions remain constant but those on acquiring foreign transactions increase, where the increase in access fees is the greatest. It is also this benchmark that sees the greatest decrease in transaction surplus, since

there is no longer an increase in merchant adoption to offset the reduction in rewards, given that m stays constant as a decreases.

1.6 Concluding remarks

The model presented in this article provides a framework for incorporating a particular source of market power in payment card markets, which results from the vertical integration of some issuers with services usually provided by acquirers within a four-party payment card network. In this context, typical interchange fee regulation consisting of a cap or a mandated value has an asymmetric effect on market participants, given that only non-integrated issuers earn that fee on consumer payments, while the margin of integrated issuers is unaffected - in fact, they may benefit from this regulation as the acquisition margin they earn on other banks' payments processed by them potentially increases as interchange fees are regulated downward. Therefore, said regulation may result in undesired effects: the model highlights that, despite the existence of marginal cost pricing to merchants and consumers on a per-transaction basis, the nonlinear fees associated with payment cards in most markets lead to other avenues through which financial intermediaries can exploit market power. The case of Argentina, while extreme in the sense that a major four-party card network relies on one firm to provide acquisition services, may serve to analyze the countervailing effects of interchange fee regulation when some parties can circumvent the payment of that fee. For example, in an assessment of its own interchange fee regulation [18], the Reserve Bank of Australia noted that local banks that were previously issuers in four-party networks formed agreements with three-party networks such as American Express in order to offer cards with greater reward schemes, unfettered by regulation on the revenue banks can raise in order to redistribute to consumers[19].

[18] Cited as Reserve Bank of Australia (2016)

[19] As a result, the RBA recommended a wider definition of 'interchange-like' payments between vertically related intermediaries within a payment card platform as a target for regulation.

The model used for analysis, while empirically tractable, relies on a host of simplifying assumptions. Some of them allow to account for variables that are generally missing from datasets available to researchers, such as rewards offered on a transactional basis. However, other results presented rely on the inflexible functional form I adopted for cardholding demand, as well as unrealistic restrictions on the functioning of the market (there is, for example, cursory evidence of surcharging card payments in Argentina, as well as credit card rewards that are funded not only by MDR revenue but also by merchants directly). Since the associated demand elasticities are crucial to a nonlinear pricing decision, it is worth considering richer demand models, such as a conventional BLP specification.

Finally, the retail banking sector of Argentina has been concurrently targeted by other policies aside from antitrust regulation directed at credit card service providers. New clearinghouses may provide mobile banking on a more accessible basis, which allows consumers to pay merchants immediately through a channel separate from conventional payment cards, greatly reducing their market power. A more complete empirical analysis that attempts to link the data with the model I presented should account for these and other developments, including not only decisions by households but also by merchants, for whom the decision of bancarization is tied to leaving the informal sector of the economy and to facing some idiosyncrasies of the local taxation regime[20]

[20]Including but not limited to accruing gross receipt tax from multiple states with card payments involving consumers and merchants from different states.

Chapter 2

Easing Business Credit Constraints Through Online Lending[1]

2.1 Introduction

Access to credit is an essential driver of firm growth and survival. It determines a business's ability to withstand economic downturns, finance daily operations and seize investment opportunities[1]. However, many economies struggle to develop financial markets that can optimally support growing businesses (Rajan and Zingales, 1998). The consequences of financial frictions, which can manifest themselves in the form of credit rationing or high interest rate spreads, are commonly exacerbated for small firms that are riskier and costlier to service (Cao and Leung, 2020; Banerjee and Duflo, 2014).

For these borrowers, online loans have continuously grown as a financing alternative to traditional banks (Wiersch et al., 2019). Virtually issued small business loans, which include direct

[1]This chapter has benefited significantly from comments and suggestions by Natalie Bachas, Bruno Baranek, Emily Cuddy, Adam Kapor, Alessandro Lizzeri, Leon Musolff, Christopher Neilson, Andy Neumeyer, Shumiao Ouyang, Daniel Paravisini, Pëllumb Reshidi, João Thereze, and participants of the Princeton IO Workshop. I am grateful to managers and staff from the lending platform for providing data and informing my understanding of their products.

[1]A classic overview of the uses of external funding in these functions is Fazzari et al. (1988)

lenders such as Kabbage or marketplaces like Lending Club designed to support peer-to-peer loans, are part of a broader category of financial technology services which has motivated a body of research on the introduction of novel credit products or risk assessment methods and their impact on financial inclusion and other outcomes of interest for Household and Corporate Finance (Branzoli and Supino, 2020). Some of the advantages attributed to online lenders include the ability to harness new sources of information on creditworthiness, to *crowdsource* costs and risks of loan origination and monitoring (Iyer et al., 2016), or to simply automate the entire process in order to create or bolster competition in markets outside the reach of traditional lenders.

This article studies the lending relationship between a large e-commerce marketplace in Latin America, and retailers from Argentina who operate on any of its platforms[2]. Marketplaces and payment processors[3] are uniquely positioned among all lenders to push the frontiers of credit access for their merchants, as they combine exclusive information that potential borrowers generate in real time with additional enforcement power, stemming from handling retailer revenue, and the ability to develop and deploy risk evaluation algorithms on a scale that might only be matched by financial entities. This enabled the marketplace I study to launch its lending arm in 2016 amid an economy where external capital is extremely scarce by international standards[4], reaching within three years a loan volume among all but its largest merchants that is on the same scale as the entirety of bank-sourced credit.

The objectives of my analysis are to characterize the extent to which this new, online borrowing alternative relieves liquidity constraints faced by retailers and to estimate the resulting impact on short and long-run revenue. First, I describe a setting where the platform issues automated loan

[2]These include an online marketplace, as well as physical retail when transactions are handled by the platform's payment processing subsidiary.

[3]Amazon Capital Services is an example in the US of a credit subsidiary operated by a marketplace, along with similar divisions of payment processors such as PayPal Working Capital and Square Capital. In China, Ant Group offers loans on all of the platforms operated by Alibaba.

[4]Reaching approximately 16% of GDP in 2017, Argentina ranks 147 out of 170 countries in the prevalence of domestic lending to the private sector. Source: World Bank

offers to affiliated marketplace retailers. This process combines proprietary risk assessment with the screening of potential borrowers through their choice of loan characteristics from a menu. Using a panel of retailers and knowledge of the offer algorithm shared by the lender, I measure an increase of retailer revenue resulting from exposure to the platform's stream of credit offers, controlling for the latter's risk assessment and credit bureau evaluations through a matching procedure.

Motivated by these estimates, as well as a platform survey which suggests that borrowers primarily require external funding to manage operating expenses, I then introduce a model of retail businesses who face occasionally binding liquidity constraints in a dynamic inventory control problem. Given a lender's imperfect knowledge of firm primitives, a business with the option of using external funds may exhibit both advantageous and adverse self-selection into borrowing through latent heterogeneity in demand, costs, and working capital. Since the retailer's policy is a choice of inventory, which acts as an upper bound on unit sales, I show that selection patterns can be highly nonlinear through an expression of a model firm's revenue quantiles conditional on firm characteristics and endogenous borrowing choices.

Finally, I reprise the previous revenue estimation within a quantile regression framework that accommodates all merchants, including long-time recipients of platform loans as well as those who might have not received a single offer yet. I augment this setup with a system of credit demand to account for endogenous withdrawal of online or bank loans and allow for latent correlation between these decisions and the realization of revenue through a vine copula model, introduced by Aas et al. (2009). This empirical model, identified by variation in the choice menus offered by the platform, enables a comparison of borrowers and non-borrowers across different retailer types as well as counterfactual analysis of business revenue when online loan offers are removed.

Throughout this article, credit constraints are shown to be prevalent among retailers and their operations are estimated to be positively impacted by the option to borrow online. Loan withdrawal rates among the cohorts of first-time online offer recipients are between 26 and 43%, and the capital injection resulting from a mean offer of half a retailer's income is estimated to increase average borrower revenue between 30 and 80%, starting in the same quarter that the offer is received. These effects persist for several quarters, in one case manifesting as an increase in the net present value of all *ex post* revenue by offer recipients[5]. Joint estimation of revenue and borrowing decisions reveals a significant positive latent correlation between withdrawal of bank and online loans in all quarters, which suggests that credit of any one type may be insufficient to satisfy business demand for external capital. In addition, there is partial evidence of advantageous selection from borrowers who withdraw online loans, a pattern pronounced among the smaller retailers of this dataset. The counterfactual analysis performed with this empirical model indicates that removing the platform's lending option, which produces loans worth up to 4% of overall revenue in my sample, results in a comparable loss of retailer sales within the same quarter even while allowing for substitution to bank loans, subject to variation in their availability.

The closest empirical study to this setting is Hau et al. (2021), which analyzes Ant Group's lending to merchants who operate in one of Alibaba's e-commerce platforms. While they control for credit access to third-party loans through retailer geographical dispersion at a larger scale than allowed by my dataset, I observe usage of bank loans directly. This enables a model where bank loans are treated similarly as online loans and either type can impact a merchant's outcomes or be informative about latent fundamental heterogeneity. More broadly, Branzoli and Supino (2020) provides a comprehensive overview of the empirical literature on financial technology (*Fintech*) services, which tackles some questions of interest that overlap with this article such as how fintech can penetrate markets underserved by traditional lenders (Jagtiani and Lemieux, 2019) or which macroeconomic conditions foster the development of fintech lending to small businesses (Haddad

[5]This happens even though my environment is not ideally suited to identify the long-run effect of improved credit access, as discussed in sections 2.3 and 2.4.

and Hornuf, 2019).

This article studies how credit constraints manifest in the retail industry. There is a vast empirical literature on the potential misallocation of firm inputs resulting from financial frictions and how this can impact productivity and employment growth. It features models of abstract production functions which span multiple industries (Midrigan and Xu, 2014; Lenzu and Manaresi, 2019; Cao and Leung, 2020), as well as studies specific to frictions in the satisfaction of firm working capital demand (Buzacott and Zhang, 2004; Kouvelis and Zhao, 2012). The latter highlight a firm's supply chain as a potential source of external funds through trade credit. While the lender I study is not a direct merchant supplier, the high return to their allocated capital in terms of increased downstream revenue together with numerous ancillary services provided to affiliated merchants[6] might render their incentives to lend more similar to a trade creditor than a financial lender's. This body of work is supplemented by a theoretical literature on the conditions under which various financial frictions emerge, such as Holmstrom and Tirole (1997) or Albuquerque and Hopenhayn (2004).

I also contribute to the methodology of Industrial Organization applied to insurance and credit contracts. Similarly to the seminal work of Chiappori and Salanie (2000), I model information asymmetries between a principal and an agent through latent correlations between the agent's choices and subsequent outcomes. My choice of Aas et al. (2009)'s vine copula provides a flexible framework to model latent heterogeneity in retailer credit and revenue outcomes spanning various orders of magnitude, and is applied to a setting comparable to recent work on quantile regressions. Arellano et al. (2017) use them to model nonlinear persistence in household income and savings decisions, and my approach can complement Arellano and Bonhomme (2017)'s work on *quantile selection* to model outcomes that may be unobservable depending on businesses' endogenous

[6]Some of these services which earn the platform additional revenue include online marketplace listings, payment intermediation for physical retailers, and merchant fulfillment.

decision to borrow.

The paper proceeds as follows. Section 2 describes the empirical setting of my analysis, including retailer summary statistics, relevant macroeconomic context, and reduced-form estimates of the impact of online loan offers. Section 3 presents my model of inventory management with financial frictions, which maps some unobservable retailer fundamentals to choices and outcomes included in my dataset. Section 4 presents my empirical model of the joint distribution of retailer credit demand and revenue output. Section 5 evaluates the counterfactual withdrawal of the platform's loan offers. Section 6 concludes.

2.2 Empirical setting

2.2.1 Data

The available data consists of a quarterly panel of 20,056 retailers operating in Argentina between May 2017 and May 2019[7]. Retailer revenue is disaggregated by broadly defined product categories and the platform in which the sale originated, including the platform's own marketplace, other online venues and physical points-of-sale. The remaining characteristics are observed or synthesized as a retailer is evaluated for potential loan offers. Some of these are exclusively observed by the platform, including a proprietary forecast of future sales and a comprehensive risk evaluation grade. Others result from a credit inquiry mediated by third parties[8] and include a credit bureau score and liabilities that the retailer incurred with any financial entity, classified by the amount of time they are past due.

[7]This sample corresponds to a fraction of all merchants eligible for loans.

[8]The credit bureau Nosis, together with information collected from the *Central de Deudores*, a public database on debtor status maintained by the Central Bank of Argentina

Table 2.1: Summary Statistics

	N_{obs}	Mean	St. Dev.	$P_{25\%}$	$P_{50\%}$	$P_{75\%}$
Retail characteristics						
Sales volume	85,804	56,173	482,773	978	3,592	20,898
Marketplace share	85,804	0.60	0.44	0.00	0.86	1.00
Public credit characteristics						
Bank loan size	18,171	56,379	566,844	312	939	3,431
Bank debt	85,804	177,003	2,939,291	0	954	4,550
Share of debt distressed[1]	64,582	0.06	0.22	0.00	0.00	0.00
Bureau score	85,804	456	223	322	477	613
Platform credit characteristics						
Offer size	44,853	31,740	62,411	898	4,021	26,964
Loan size	7,025	8,441	20,909	566	1,714	6,850
Maturity (months)	7,025	9.0	3.6	6.0	12.0	12.0
Interest rate (p.p.)	7,025	67.65	25.37	43.00	62.00	84.00

Notes: Retailer characteristics by quarter. Monetary values are reported in current USD. Sales are observed for every retailer-quarter; share of distressed debt is reported for each retailer-quarter with positive liabilities; the lender's offer size is quoted for each retailer-quarter with at least one platform loan offer; maturity and interest rate correspond to each accepted platform loan offer.

[1] Debt stock is classified as distressed if it is over 90 days due (*situación 3* or higher as reported in the BCRA *Central de Deudores)*

Sample characteristics are summarized in table 3.1. Nearly all observed retailers are micro or small businesses[9] and 83.3% of them unincorporated[10], although this observation belies substantial heterogeneity in retailer size as the first and last decile of quarterly revenue span four orders of magnitude. The sales volume of a business plays an important role to determine the size of subsequent loans: banks require income information when a business applies for various types of loans; if a proprietor is borrowing on a credit card, the borrowing limit will usually be indexed to their personal income. In the case of platform loans, the size of a loan offer is tied to recent revenue generated by a retailer on its platforms.

[9]The Argentine Ministry of Production issued threshold definitions for business size during 2018. Micro businesses may earn a three-year moving average of quarterly revenue of up to USD 167500, with the corresponding cutoff for small businesses set to USD 1017500.

[10]For businesses of this size the most commonly occurring corporation is a limited liability company (SRL, by its Spanish abbreviation).

Credit history is another variable that determines a retailer's borrowing opportunities. The median credit bureau score of 477 characterizes a potentially risky borrower, whose options for a traditional bank loan might be limited. Table 3.4 shows the frequency of loan withdrawal for retailers above and below the median credit score who had the option of accepting a platform loan offer in a given quarter. Although low-risk retailers borrow at the same rate as their high-risk counterparts, the latter are twice as likely to do so through an online source. This pattern has been documented in other settings, such as the United States in recent years sbcs2018. This informs one of three observations relevant to the rest of my analysis:

Retailers may experience liquidity constraints in the form of quantitative credit rationing from traditional and online lending sources, as well as through significant spreads between saving and borrowing interest rates.

Table 2.2: Take-up rate of bank and platform loans

High-risk retailers				Low-risk retailers			
		Platform loan				Platform loan	
		Yes	No			Yes	No
Bank loan	No	15.4%	65.0%	Bank loan	No	7.6%	64.6%
	Yes	5.2%	14.2%		Yes	3.5%	24.0%

Notes: Cross tabulation of platform and bank loan withdrawal rates for retailer-quarters where a platform loan offer is produced. *High-risk retailers* are those with a credit bureau score below the whole-sample median of 477 and *low-risk retailers* the complementary population.

Based on their relatively short maturity of up to a year, the marketplace's merchant loans are working capital loans which stores most commonly employ to restock their inventory between peaks of retail demand. The exact composition of a retailer's bank debt is not included in this dataset, but aggregate statistics published by the Argentine central bank[11] reveal that the loan type may depend on whether the retailer is an individual or incorporated. The prevailing loan type among the former is credit cards, balances on which are typically repaid in fixed installments of

[11] Published as part of the *Cuadros estandarizados de series estadísticas*, under monthly volumes lent to the non-financial private sector.

up to 12 or 18 months through a government-sponsored program[12]. While proprietors of small enterprises may also borrow through credit cards, the main component of corporate debt is current account overdrafts, which are issued with a much lower maturity oscillating between 35 and 50 days on average throughout the sample; average overdraft interest is included in figure 2.1 as *SME lending rates*.

The distribution of loan volume, both on and off-platform, is highly skewed and emphasizes the platform's specialization in smaller loans issued to risky borrowers. While total amounts lent by financial companies exceed platform loans by more than an order of magnitude (1.02 billion vs. 58 million USD), for all but the largest 5% of bank borrowers the platform is a significant creditor with loans worth 16 million USD as opposed to 57 million generated from banks. In addition, platform loans are generated through offers which enable recipients to choose how much to borrow up to a limit. Notably, 56% of all such loans are issued at the borrowing limit, which indicates that many retailers may find their demand for external funds unmet. The main source of funding that is missing from this dataset is trade credit, which is typically measured as accounts payable that a store maintains with upstream suppliers and has a maturity comparable to bank overdrafts.

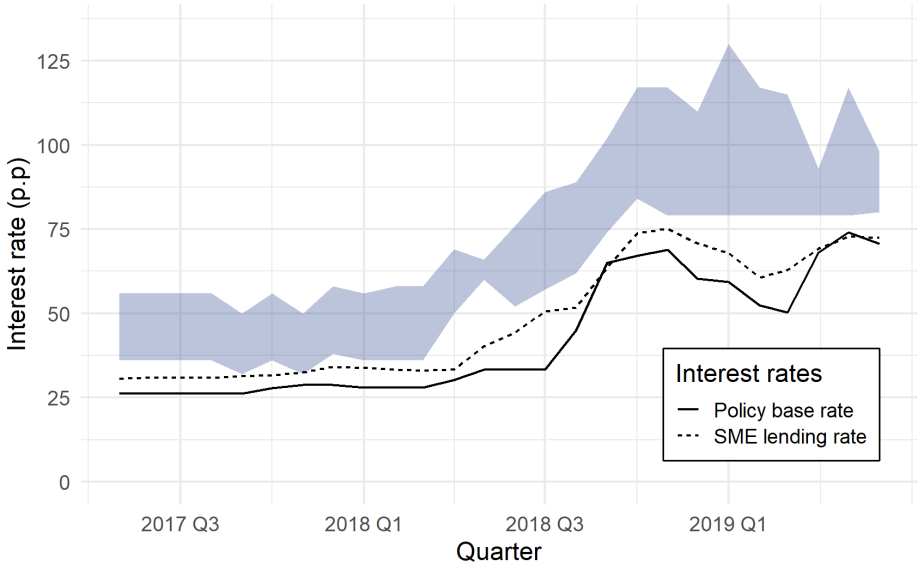
2.2.2 Aggregate sales and credit patterns

Some trends in Argentina's macroeconomic performance andthe platform's operation during this period provide additional context. Following presidential elections in 2015, the federal government and central bank pursued a policy of integration with international capital markets combined with monetary policy that has been variously described as inflation targeting and interest rate-based stabilization[13]. While inflation rates remained at high levels, increasing from 25.7% in 2017 to 34.3% in 2018 and 50.1% in 2019, shifts in the policy interest rate and instrument preceded significant volatility in nominal and real interest rates that spilled over to the rest of the

[12]Called *Ahora 12*, the details of which can be found online at https://www.argentina.gob.ar/ahora-12

[13]The former term is used in an *ex post* account by a former BCRA president Sturzenegger (2019) and a subsequent counterpoint Di Tella (2019); the latter is mentioned by Calvo (2017).

Figure 2.1: Interest rates



Notes: Selected interest rates for the May 2017-Jun 2019 period. The solid line is a reference rate for monetary policy. Until Aug 2018, it was defined as the midpoint between the active and passive rate for seven-day loans between the Central Bank and the private banking sector; afterwards, this rate was replaced by the Leliq's, a security of identical maturity whose secondary market is restricted to financial entities. The dashed line indicates the average current account overdraft rate for small and medium enterprises; this type of loan comprises 87% of SME debt in domestic currency. The blue shaded area represents the interval between the 10th and 90th percentile of interest rates attached to platform loan offers.

local financial sector as shown in figure 2.1. Domestic borrowing experienced a brief increase in 2016 and 2017 but collapsed in the following year as highlighted in figure 2.2.

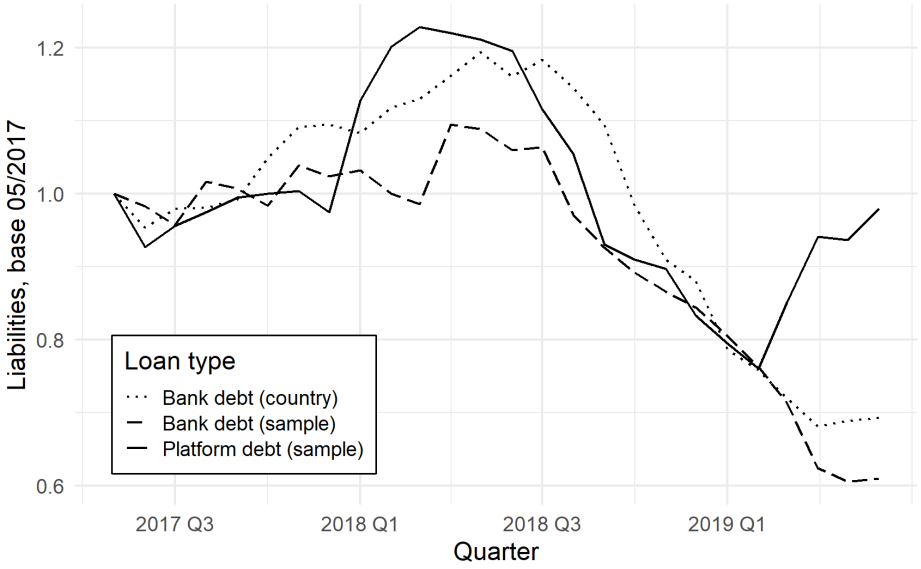
Amid these developments, the marketplace I study experienced substantial growth in Argentina as well as other Latin American markets. Its merchant credit service was deployed in parallel to the penetration of payment services offered by the platform. By the initial date of my panel in 2017, its online marketplace was already a mature platform where over 90% of payments were processed by the company itself. In contrast, off-marketplace payments handled by the company experienced a rapid, persistent increase throughout the analyzed period as highlighted in figure 2.3. This observed increase was mediated not only by revenue growth but also by changes in the adoption of various payment services by physical retailers, including mobile points-of-sale and

QR transactions, as well as consumers, who access this environment through digital wallets and a credit card issued by the platform in association with a retail bank. Since changes in this adoption rate condition the data I can observe, the remainder of my analysis will focus on marketplace transactions, where the platform's presence is absolute throughout the panel.

There is a retail cycle, with peaks of revenue spaced at least a quarter apart.

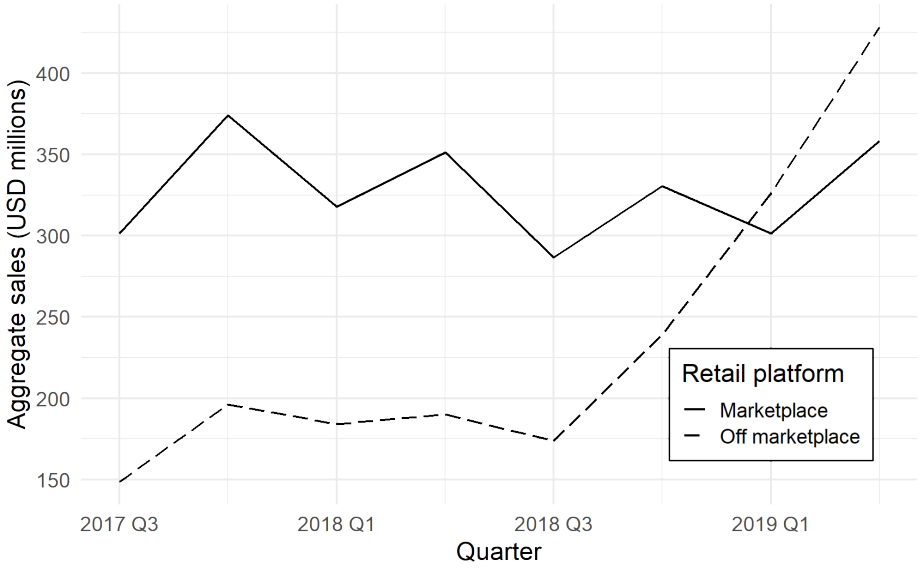
The marketplace revenue series in figure 2.3 highlights the existence of a retail cycle. Sales volume for many businesses in Argentina is punctuated by the *aguinaldo*, a thirteenth wage paid in two installments scheduled at June and December. It is not uncommon for retailer sales to surge over 50% of the yearly average in the month preceding this transfer, and many small businesses cite the seasonal mismatch between revenue and costs paid to accumulate inventory beforehand as a reason to draw on working capital loans.

Figure 2.2: Aggregate debt levels



Notes: Average liabilities for the May 2017-Jun 2019 period, denominated in inflation-adjusted domestic currency and scaled relative to May 2017 levels. Initial platform debt is ARS 88.8m across 1235 retailers; initial bank debt in sample is ARS 3.17b across 5058 borrowing retailers. The dotted country line corresponds to total domestic currency liabilities in the same period.

Figure 2.3: Aggregate retailer revenue



Notes: Aggregate retailer revenue by retail platform, denominated in current dollar amounts for each quarter. Marketplace transactions are performed on the platform's website. Off-marketplace transactions are processed through its external payment processing service and may originate in physical retail venues, other online marketplaces, or mobile points-of-sale.

2.2.3 The platform's lending algorithm

The platform's comparative advantage in lending to the analyzed retailers lies in their working relationship mediated by marketplace and payment processing services and is characterized by both proprietary information and additional enforcement power. Through them, this would-be lender gathers comprehensive data on merchants who operate in its online marketplace, including not only their revenue stream but also thousands of variables on consumer interaction down to the level of individual transactions. In the case of off-marketplace merchants[14], the platform requires that they offer consumers the option to transact through its platform's payment service. This ensures that revenue information becomes more detailed as consumer adoption grows on the other side of the market and grants the platform the ability to withhold monthly installment payments

[14]Loans to mPOS merchants were offered starting in the second half of 2018.

on any realized loans before merchants can withdraw revenue to a traditional bank account.

Instead of accepting loan applications, the platform issues loan offers automatically to eligible merchants who can then choose how much to borrow (if at all) and how many installments in which to repay the loan. After 30 days, the offer expires and the retailer is reassessed for eligibility. Once an offer is accepted, funds are credited to a retailer's checking account within 2 to 5 business days. The maximum principal and maturity of this loan, as well as the interest rate, are designed by the platform with consideration given to a scoring algorithm. This system mirrors the task of a conventional loan officer attempting to identify borrowers who are able and willing to repay a loan. Some inputs to this algorithm are constructed from the platform's private information and include a sales score, predictive of a retailer's repayment capacity, as well as the retailer's repayment history for any previously issued platform loans[15]. Others, such as the aforementioned credit bureau score, are purchased in bulk from third parties or retrieved from public central bank databases.

Since some of this information is costly to acquire, the platform proceeds through stages to identify offer recipients. A preliminary condition, publicly announced, is that retailers maintain a sales volume over a given threshold for a certain period of time[16], good reputation on relevant sales platforms, and good standing in the repayment of any previously issued loans. This is followed by a periodic acquisition of credit reports and a more comprehensive evaluation of the retailer's marketplace performance, after which the lender decides whether or not to extend a loan; if it does, the offer corresponds to one of up to seven risk grades that match the previous evaluation.

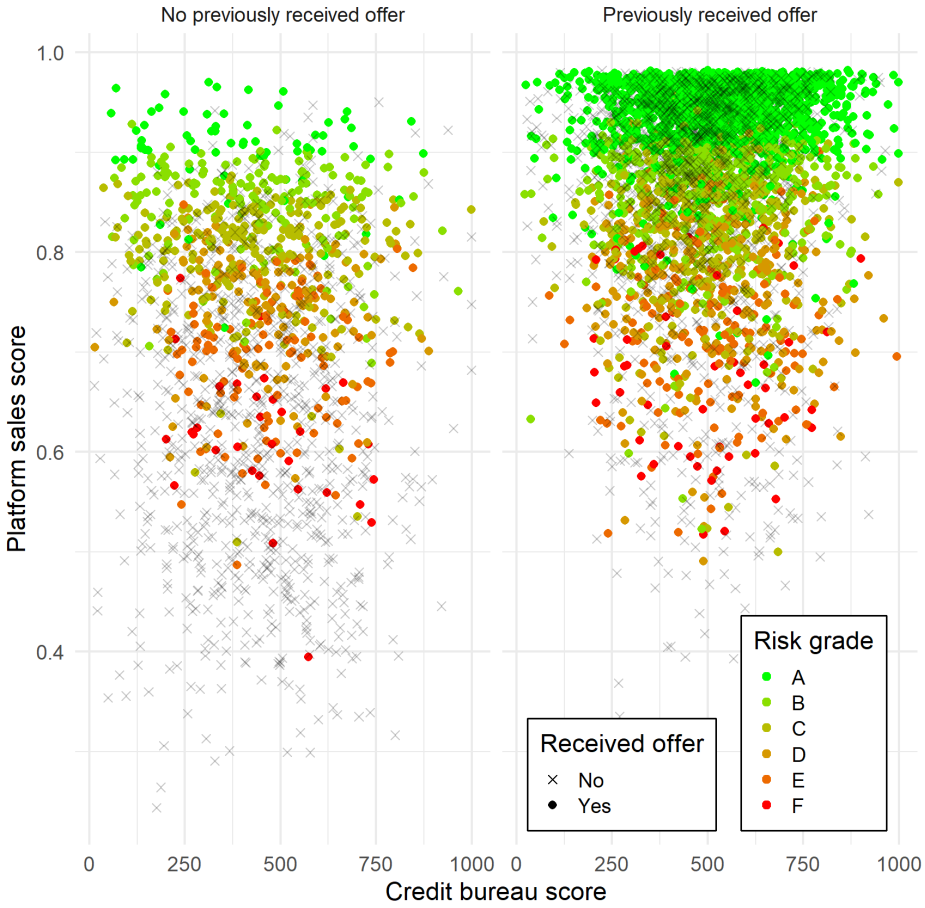
A feature of my analysis is that these interim scores are observable before the decision to extend an offer is made, which enables various comparisons between offer (non-)recipients. Figure 2.4 projects the risk grades and offers of a single quarter onto sales and credit bureau scores to illustrate their distribution. The Appendix elaborates on the estimation of a generalized boosting regression

[15]This data is reported back to credit bureaus, however, which allows for informational spillovers.

[16]For example, the threshold quoted in 2021 is of 1000 ARS in monthly sales for at least three months

where I control for these and other variables to produce propensity scores for the receipt of a loan offer in a given retailer-quarter. A mean AUC score of 0.82 indicates that this model is a good predictor of loan offers, although its quality varies subject to some conditions.

Figure 2.4: Distribution of loan offers and risk grades



Notes: Scatter plot of retailer credit bureau scores and platform-exclusive sales forecast scores, during quarter 2 (2017 Q4) of the panel. The left panel of this figure includes retailers who had never received a platform offer before this quarter; the right panel includes the remainder. Quarter 2 offer recipients are denoted by a dot, the color of which indicates the attached risk grade, while offer non-recipients are marked with a cross. Note the mass of non-recipients with high scores who had previously received a loan offer: the majority correspond to retailers who withdrew a loan and are in the process of repaying it.

2.2.4 The impact of a loan offer

Retailers report demand and usage of external funds primarily to finance inventory purchases, and there is strong evidence of an immediate positive impact of the platform's loan offers on retailer revenue.

As it launched its merchant credit service, the marketplace surveyed retailers on its platforms to determine the prevalence of liquidity constraints and how they impacted merchant operations. 75% of respondents needed additional funds and only 18% could gain access to a loan from a financial company. The platform cannot compel retailers to spend its loans on business assets, but two thirds of borrowers reported using them to accumulate inventory in anticipation of retail cycles and inflation that might mitigate the real cost of financing.

The implementation of the platform's lending algorithm described in the previous section enables an assessment of the impact of additional financing options on retailer revenue. Each quarter, new retailers are inducted as potential loan offer recipients following a credit pull and scoring evaluation. Some of these merchants receive their first platform loan offer, whereas the remainder can only resort to a bank loan, if one is available - the former will be considered as a treatment group to evaluate the effect of exposure to an additional financing option in a given quarter.

The identifying assumption I will employ to estimate this effect is that offer recipients are selected on observable characteristics, particularly the ones used to estimate the propensity score from the previous section. The relevant variables for a retailer that might receive their first loan offer are their size, measured by their sales in the previous quarter, current liabilities to the financial sector, their credit bureau score, and their platform-assigned sales score[17]. I will also restrict this evaluation to retailers with an observable credit score below the whole-sample median of 477: this

[17]This excludes the platform credit history that a retailer generates once they *accept* or *reject* at least one loan offer, since this information is unavailable for first-time recipients.

has the dual purpose of highlighting the effect on retailers most likely to face concurrent liquidity constraints and increasing overlap between offer (non-)recipients[18]

To estimate treatment effects, I create a control group by matching the treated retailers in each quarter with other retailers who have been scored by the platform but have not yet received a single loan offer based on observable covariates. Table 2.3 reports bias-adjusted average treatment effects on the treated retailers according to the matching estimator proposed by Abadie and Imbens (2006) for four cohorts and six different outcomes: (log) revenue in the same quarter the loan offer was produced and each of the three subsequent quarters, net present value of all revenue earned during and after treatment and revenue two quarters before treatment for robustness.

Table 2.3: Matching estimates of treatment effects by cohort

Cohort	$t-2$	$t-1$	$t+0$	$t+1$	$t+2$	$t+3$	$\log(NPV)$
$t=1$	0.07	—	0.00	0.04	0.15	0.03	0.08
($N_{tr}=390$)	(0.14)		(0.10)	(0.16)	(0.16)	(0.22)	(0.16)
$t=2$	-0.02	—	0.10	0.26	0.24	0.18	0.11
($N_{tr}=551$)	(0.04)		(0.04)	(0.09)	(0.10)	(0.13)	(0.07)
$t=3$	-0.09	—	0.16	0.26	0.20	0.15	0.20
($N_{tr}=497$)	(0.07)		(0.05)	(0.10)	(0.12)	(0.17)	(0.06)
$t=4$	0.02	—	0.16	0.14	0.06	0.22	0.08
($N_{tr}=339$)	(0.12)		(0.07)	(0.11)	(0.21)	(0.13)	(0.21)

Notes: ATT estimates of revenue change induced by increased credit access through receipt of the platform's first loan offer. Columns indicate outcomes by offset relative to the date of first offer, from -2 to +3 quarters (no estimate is reported for $t-1$ since this quarter's revenue is used as a matching variable) and the NPV of all *ex post* revenue. Rows indicate different cohorts, who received their first offer during one of the initial four quarters of the panel. The number of treated retailers in each cohort is denoted as N_{tr}. The first cohort of this evaluation is a notable outlier, since it includes one of the seasonal peaks of the retail cycle in May 2017 and yet no significant short-term effect is estimated. A likely cause for this is the marketplace's cautious lending behavior during *aguinaldo* months, in which they focus their offers on retailers previously inducted into the lending program.

[18]The resulting slice of retailers, for example, is entirely compatible with the design procedure detailed in Imbens (2015), which prescribes the exclusion of units with an extreme estimated propensity to (not) receive a treatment in order to increase overlap and reduce the variance of a matching estimator.

This estimation suggests that the platform's offers have an immediate impact on merchant revenue and that this effect may be prolonged over several quarters. A key channel that could mediate this effect is the high acceptance rate of online loans in the treatment groups, which lies between 26 and 43% across cohorts and is thus between two and three times the whole-sample average. For reference, if the platform's offer is used as an intent to treat retailers with realized loans, the estimated impact of loan withdrawal on borrowers is a relative increase of revenue between 30% and 80%. This effect is on the same scale as the maximum principal that these offers allow retailers to withdraw, which on average amounts to 50% of revenue in the preceding quarter.

While the net present value of all *ex post* revenue is higher is significantly higher for the third cohort under evaluation, evidence of the long-run impact of credit access on retailer outcomes is limited by the definition of treatment and control groups in this comparison. Since all retailers in the control group have been scored by the platform, many of them are considered for future offers, with as many as 50% of them receiving an offer within two quarters of the corresponding treated group.

The previous three *observations* summarize an environment where retailers function as businesses with large working capital requirements relative to their revenue and may lack external funding to cover operating expenses. Equipped with strong evidence that this platform's loan offers increase concurrent store sales for borrowers, the analysis in the next section will elucidate the characteristics of a firm which drive it to borrowing states in order to inform an estimator which generalizes the results of this section to the entire sample of retailers.

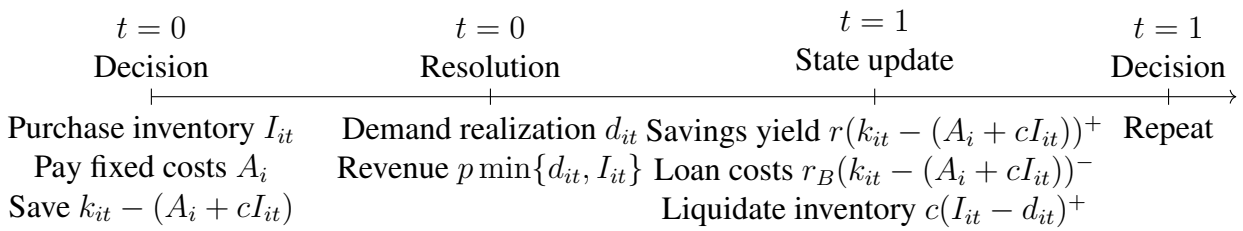
2.3 Theoretical framework

2.3.1 A model of inventory management

A model that combines liquidity constraints with inventory management, a primary determinant of credit demand according to retailer surveys, provides a framework where the platform's lending initiative may mediate short and long-run growth of retailer revenue. In this section, I develop an iterated *newsvendor* model to understand the joint distribution of revenue and borrowing choices and discuss some challenges to make inference on these variables with the available data.

In the taxonomy of inventory management models provided by Pyke et al. (2001)[19], the newsvendor setup is appropriate to describe the problem of a retailer who makes a single restocking decision in advance of a brief *selling season*, a point at which the actual realization of demand remains uncertain. The timing of decisions in this model is displayed in figure 2.5. An iterated newsvendor problem can then be understood to describe the behavior of a retail who faces a sequence of selling seasons; the single state variable that captures the dynamic features of this model is the retailer's working capital k, accumulated through profitable sales in each period.

Figure 2.5: Inventory model timing assumptions



The objective of a retailer is to maximize the net present value of expected profits across all periods, discounted by the saving interest rate r. The main simplifying assumption I adopt to com-

[19]Depending on the focus of the analyst, one of many other *item control systems* may be adopted. If inventory review is costly, one might choose to focus on the choice of a review interval R to adopt; alternatively, if restocking inventory carries a fixed cost an optimal policy might consist of a lower threshold s where inventory is restocked to the order-up-to quantity S.

pute this expectation is that every retailer knows their demand D_{it} to be distributed i.i.d according to a cdf F_i. The value of this firm can then be expressed as the solution of a Bellman equation for $V(k)$, a function of working capital k together with a law of motion for capital $k'(k, I, x)$ which depends on its last realization k, the retailer's choice of inventory I, and realized sales x[20]:

$$V(k) = \max_{\{I\}} p\left(\int_0^I x f_i(x)dx + I(1 - F_i(I))\right) - A_i - cI - \frac{r_B - r}{1+r}(A_i + cI - k)^+ + \frac{1}{1+r}\left(\int_0^I c(I-x)f_i(x)dx + E_X[V(k'(k, I, x)]\right)$$

$$k'(k, I, x) = k - A_i + (p(1+r) - c)\min\{I, x\} - r_B(A_i + cI - k)^+ + r(A_i + cI - k)^-$$

Costs are summarized by a constant unit cost c for each unit of inventory and a fixed cost of operation A_i paid every period. I assume inventory to be extremely liquid: any unsold units can be returned to the supplier at cost c following the selling season. However, costs have to be paid in advance of sales: if a retailer cannot cover restocking expenditures out of their own working capital k they will borrow the difference, to be repaid at a borrowing rate r_B. Liquidity constraints exist whenever $r_B > r$.

The main trade-off a retailer faces when purchasing additional stock is between the profit margin of an uncertain sale and the opportunity cost of unsold inventory. In this model, this cost derives solely from timing assumptions: even though any remaining stock at the end of the selling season is recovered at cost, this happens a period after purchase and thus the cash flow is discounted[21]. The most explicit formulation of this trade-off attains when $r_B = r$, in which case the resulting optimal inventory policy is to stock up to a constant quantile of the demand function in every period as established by Arrow et al. (1951):

[20] Y^+ is shorthand for $\max\{Y, 0\}$

[21] More stringent *overage* costs stemming from unsold inventory include explicit storage costs or supplier discounts when returning stock. Assuming that demand above inventory capacity is lost implies a high *underage* cost: in other specifications, order backfilling is allowed and excess sales are simply fulfilled with a delay and/or a price discount.

$$p(1 - F_i(I)) = c(1 - RF_i(I)) \tag{2.1}$$
$$I^* = F_i^{-1}\left(\frac{p-c}{p-Rc}\right)$$

2.3.2 The effect of financial frictions

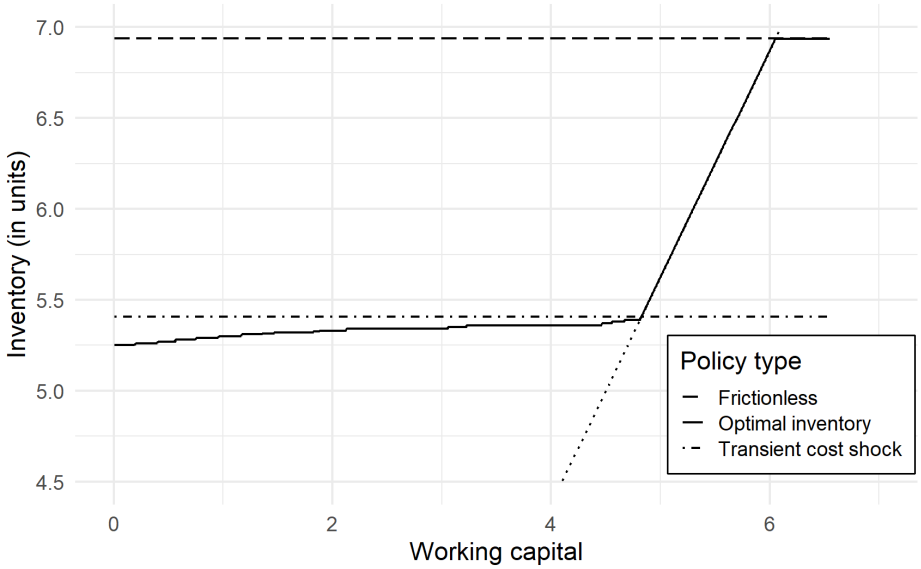
When liquidity constraints exist, external financing is more expensive for the retailer and working capital becomes a valuable asset. It increases current profits in proportion to the interest rate spread $r_B - r$ whenever expenditures exceed available cash. This renders the value of the firm $V(k)$ an increasing and concave function of k and impacts the optimal choice of inventory by modifying the weights of each term in equation 2.1. By applying an envelope theorem, the first order condition for any interior solution can be formulated for any value of r_B as:

$$p(1 - F_i(I^*))[1 + V'(k'(k, I^*, I^*))] = c[1 + V'(k)] - Rc\int_0^{I^*}[1 + V'(k'(k, I^*, x))]f(x)dx \tag{2.2}$$

This first-order condition generally results in a more conservative choice of inventory. Intuitively, a marginal addition to inventory only produces revenue if demand is high enough to exhaust the retailer's stock, in which case the firm is richer and thus the marginal value of additional capital in the store's coffers is less valuable (this happens if selling the entirety of optimal inventory is profitable even under the strain of external financing, i.e. $k'(k, I^*, I^*) > k \quad \forall k$). The optimal inventory policy with financial frictions can be described in three parts as in figure 2.6: if working capital is high enough, the unconstrained solution of equation 2.1 is optimal; immediately below the threshold for this solution, the retailer will spend all of their working capital but will not borrow to accumulate additional inventory; below a second threshold, the retailer will borrow to

meet the inventory level in equation 2.2.

Figure 2.6: Optimal inventory policy



Notes: Example solution of an optimal inventory problem, computed by value function iteration. The horizontal axis indicates the state variable k, the retailer's cash before committing to an inventory purchase I, represented in the vertical axis. Parameters of the retailer's objective function are $p = 1.15, c = 0.8, A = 0.5, r = 0.05, r_B = 0.2$. The potential demand function is parametrized as $d_{it} \sim N(5, 1.5^2)$. The diagonal dotted line depicts the policy $I = \frac{k-A}{c}$ where the entirety of working capital is used to purchase inventory, without borrowing additional amounts. Also shown are a 'frictionless' policy corresponding to the solution of equation 2.1, and a 'transient cost shock' policy where the right hand side of equation 2.1 assumes the form $c(1 + R(r_B - r) - RF_i(I))$, adjusting the initial marginal cost paid by the discounted interest rate spread.

A hypothetical scenario provides a good approximation to a borrower's choice of inventory. If all parameters are such that a retailer expects that they would only need to borrow on the current period and no future periods to satisfy their inventory needs, the resulting first-order condition matches that of equation 2.1, except that the current marginal cost is adjusted upwards by the discounted interest rate spread, $(r_B - r)(1 + r)^{-1}$. The resulting choice is labeled as a *transient cost shock* policy in figure 2.6, and reduces the impact of borrowing to a single-period shift in marginal costs.

2.3.3 Model results in context

The inventory model outlined above provides a characterization of firms who occasionally face financing constraints and may transition in and out of borrowing[22]. The revenue process for these businesses immediately distinguishes between retailers who borrow and those who don't but are otherwise identical: the former accumulate lower inventory due to the additional burden of external finance on marginal costs and thus place a more binding upper bound on their sales revenue on the same period that they borrow.

The salient attribute of borrowing options that impacts retailer choices and revenue is the loan's interest rate; however, if quantitative borrowing limits exist they will depress firm revenue further relative to a scenario where they are absent. The available data suggests that both of these factors are a significant source of financial frictions: if the turnover period of inventory matches the quarterly frequency of observations, the interest rate spreads documented in figure 2.1 account for an upwards cost shift of up to 15%, while 56% of platform loans are issued at the observable borrowing limit assigned to the matching offer.

Although my analysis focuses on credit demand by businesses, there is substantial research on credit suppliers and conditions under which the assumed financial frictions of this model emerge. Albuquerque and Hopenhayn (2004) builds a competitive lending framework around a firm which requires an initial capital injection followed by ongoing investments to continue operation. Under limited liability, firm owners could profitably default on long-term loans, so the authors treat the value of the firm as a contractible object and characterize the efficient degree of revenue sharing that maximizes firm growth and survival. In a more specific analysis of retailer supply chains, Kouvelis and Zhao (2012) develop a model that features not only a competitive banking sector to generate short-term financing but also a wholesale supplier who can provide trade credit, in either case under a similar threat of default by the borrower. The authors show that vertical linkages

[22]The existence of fixed costs A_i is assumed to keep the capital process from being monotonically increasing.

equip suppliers with an incentive to lend under better terms than even a perfectly competitive fringe of banks. Since the marketplace charges merchants for various ancillary services, this relationship may further explain the platform's engagement with merchants otherwise excluded from working capital loans, and this model motivates a perspective of their lending as a hybrid of a financial product and an instrument of supply chain coordination.

The newsvendor problem in this section highlights many variables that remain unavailable in the dataset I analyze. Significantly, only revenue is tracked rather than unit sales and retail price, and merchants' inventories and working capital are unobserved. While this precludes a direct estimation of this model[23], some of its predictions invite further analysis. The optimal choice of inventory, which is in many cases approximated by a fixed quantile of a retailer's potential demand function, establishes a link between the fine variation I observe in platform loan menu characteristics and the contemporaneous distribution of merchant revenue: the uppermost quantiles of borrower revenue should be smaller than comparable non-borrowing retailers and a higher interest rate should widen this gap.

A final observation on this inventory model concerns the informational assumptions made on firms, potential lenders, and a third-party observer. As discussed in section 2, some information about the creditworthiness of a retailer is widely available to all lenders, while other variables are exclusive to the platform and rendered available for my analysis. Even from the platform's point of view, however, a retailer's choice to borrow or not can be informative about model fundamentals. From the short-term approximation to equation 2.2, the binary variable b_{it} that indicates whether a retailer borrows in a given quarter and their revenue y_{it} can be expressed as:

[23]Some relevant examples of structural estimation of inventory models include Olivares et al. (2008), which estimates a straightforward version of the newsvendor model to model hospital operating room reservations and Aguirregabiria (1999), which accounts for retail demand to explain joint patterns in the distribution of store inventories and markups through a slightly different supply chain model, featuring fixed costs of restocking.

$$b_{it} = \mathbf{1}\left\{k_{it} < A_{it} + c_{it}F_i^{-1}\left(\frac{p_{it} - c_{it}(1 + R(r_{B,it} - r)}{p_{it} - Rc_{it}}\right)\right\} \tag{2.3}$$

$$y_{it} = \log(p_{it}) + \min\left\{\log(d_{it}), \log F_i^{-1}\left(\frac{p_{it} - c_{it}(1 + \lambda_{it})}{p_{it} - Rc_{it}}\right)\right\} \tag{2.4}$$

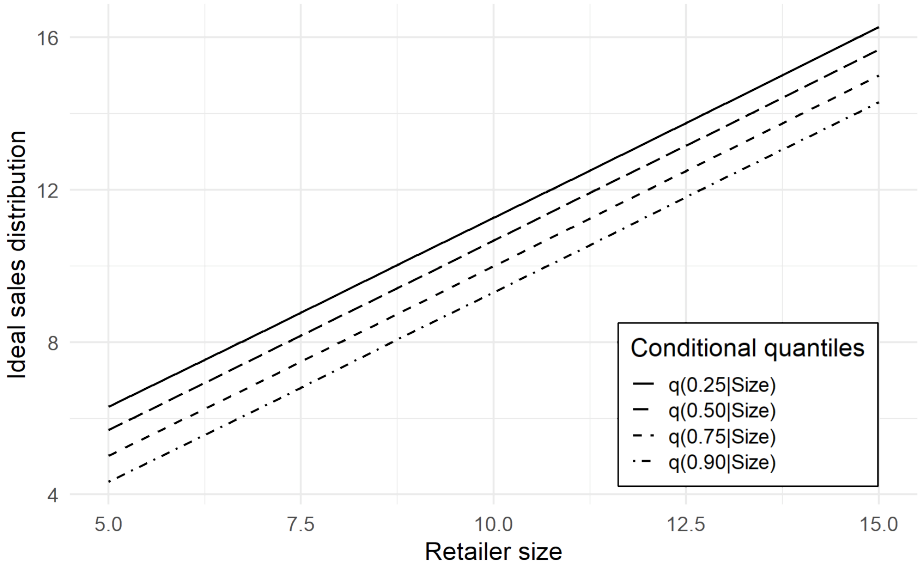
The borrowing threshold combines information about the retailer's working capital, markups and demand function. Notably, any first-order stochastic increase in the demand distribution makes the retailer more likely to borrow and is thus a source of positive selection to the extent that it is known by the merchant and unknown by other agents. For equation 2.4, d_{it} is a realization of potential unit sales demand and λ_{it}, bounded by 0 and $R(r_{B,it} - r)$, captures the cost shock implied by borrowing constraints. λ is equal to 0 when the firm has an interior solution without borrowing for its first-order condition in equation 2.1 and equals $R(r_{B,it} - r)$ instead for an interior solution with positive borrowing.

Figures 2.7 and 2.8 illustrate a simulation of the newsvendor model during a single period according to two scenarios. Under the assumption of *no unobserved heterogeneity*, an observed covariate is a sufficient statistic to explain the distribution of unit demand F_i, the retailer's expected potential sales (labeled as 'size' in the figures); in the case of *unobserved demand heterogeneity*[24], retailer size is shifted by mean-0 symmetric noise, observed by the retailers but unknown by other agents. Figure 2.8 shows how the distributions of borrowers and non-borrowers compare conditional on size by introducing conditional quantiles of the sales distribution, defined as $q_i(u|X) = F_i^{-1}(u|X)$ for $u \in [0, 1]$. It highlights the presence of both a behavioral impact on borrowers due to cost increases from present and expected future loans, as well as the selection effect resulting from the influence of unobserved demand on the borrowing threshold. In this light, the empirical model in section 4 is an attempt to estimate the joint distribution of firm revenue and

[24]Note that other sources of unobserved heterogeneity might exist, as shown in equations 2.3 and 2.4

credit while accounting for the latent distribution of working assets, demand, and cost shocks that might remain unobserved.

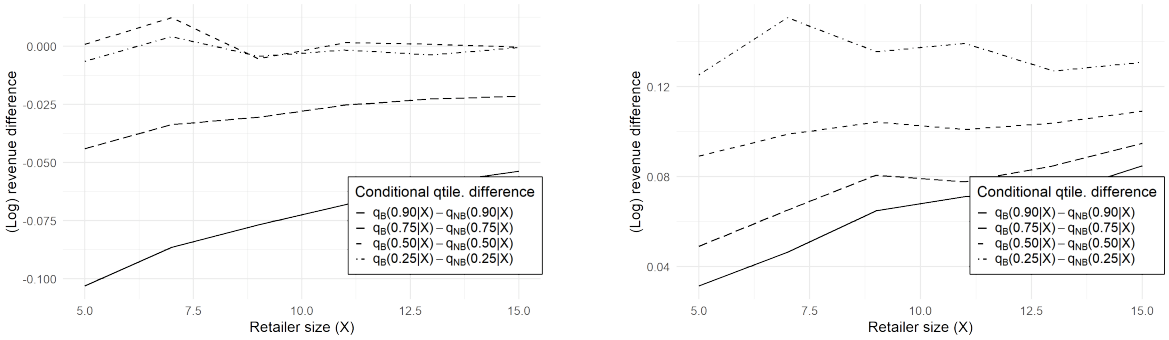
Figure 2.7: Conditional distribution of fictitious demand, no unobserved heterogeneity



Notes: Selected quantiles of the demand distribution for retailers with observed demand heterogeneity. Conditional on observed retailer size X_i, their demand is distributed $d_{it}|X_i \sim N(X_i, 1.5^2)$.

2.4 Empirical model

The previous sections outline a setting where firm outcomes respond positively to the alleviation of liquidity constraints. The reduced-form estimation in section 2 suggests that exposure to online loan offers increase the revenue of retailers on the platform in an immediate and persistent fashion. Based on platform surveys pointing to inventory accumulation as the primary destination of these loans, the model in section 3 describes firms that experience periodic working capital shortages and how improvements in their terms of lending, such as lower interest rates or higher borrowing limits, lead to higher revenue. Moreover, imperfect information about the retailer's demand and markups renders the borrowing threshold as informative not only of working capital shortages but



(a) No unobserved demand heterogeneity (b) Unobserved demand heterogeneity

Figure 2.8: Difference in borrower and non-borrower revenue quantiles, inventory model

Notes: Difference between borrowers and non-borrowers of the distribution of *realized* retailer unit sales, assessed at four quantiles. In the leftmost panel, all heterogeneity is observable and the only difference between non-borrowers and borrowers is that the latter choose a lower inventory capacity, which binds their sales at the top end of the distribution. In the rightmost panel, unobserved stationary variation is added to retailer size, now $X_i + \varepsilon_i$ with $\varepsilon_i \sim N(0, 0.1(X_i)^2)$, which induces advantageous selection into borrowing by retailers with high unobserved demand. All other parameters are fixed to the values in figure 2.6. To generate both borrowing and non-borrowing retailers, for each value of X_i retailers were seeded with working capital uniformly distributed between 95% and 120% of the borrowing threshold in equation 2.3, although F_i is only conditioned on observable X_i.

also other primitives of the inventory model, as highlighted in equations 2.3 and 2.4.

In this section, I propose an empirical model to estimate the joint distribution of retailer revenue and borrowing that reflects their relationship in the inventory model. Its main feature is that I allow for latent correlations between retailer choices and outcomes, which serves at least two functions. The first one is as a test for the extent of information private to retailers in this model, from the perspective of both the platform and outside lenders. Aside from assessing the parameters governing latent correlations between an agent's choices and outcomes, as in the seminal work of Chiappori and Salanie (2000), this test proceeds by comparing the distributions of borrowing and non-borrowing retailer revenue to a sharp prediction of the inventory model with minimal asymmetric information. If the only information exclusive to firms is their working capital, then borrowers simply accumulate lower inventories than an observably identical non-borrowing counterpart due to the implied marginal cost shock. As a consequence, their revenue should be lower and this decrease should be more pronounced at higher quantiles of its distribution, where the

choice of lower capacity bounds potential sales as shown in panel (a) of figure 2.8. The second purpose of this model is to evaluate the impact of the platform's novel lending product on a wider population than the estimator of section 2. By exploiting the fact that the platform's loan offers are assigned according to observed variables, I can separately estimate retailers' borrowing choices in menus that include online loan offers and those that do not, and employ those estimates to perform counterfactual analysis, which will be elaborated further in section 5.

2.4.1 Elements of the empirical model

I consider a panel of retailers $i = 1, ..., N$ observed during 8 quarters and focus on three endogenous variables: a retailer's quarter-t revenue y_{it}, an indicator of whether a platform loan is accepted in the current quarter b^1_{it} and a similar indicator for a bank loan, b^0_{it}. Revenue is modeled through its conditional quantiles $q(.|x)$; borrowing is represented through the propensity to borrow P from each possible source:

$$y_{it}(x^Y_{it}, u_Y) = q(u_Y|x^Y_{it}) = p\left(x^Y_{it}\right)' \beta_t(u_Y) \tag{2.5}$$

$$b^0_{it}(x^0_{it}, u_0) = \mathbf{1}\left\{u_0 < P_{0,t}(x^0_{it})\right\} \tag{2.6}$$

$$b^1_{it}(x^1_{it}, u_1) = \mathbf{1}\left\{u_1 < P_{1,t}(x^1_{it})\right\} \tag{2.7}$$

The specification for revenue draws from the quantile regression framework, with a basis of third-degree polynomials for covariates x^Y_{it} which include retailer i's product category, an indicator of whether the retailer is a person or an incorporated business, their last realization of revenue $y_{i,t-1}$, the platform's predictive sales score, and contemporaneous loans from either source. Equation 2.5 is a flexible modeling tool which can capture the impact of borrowing on different quantiles of revenue. This is desirable since the terms of lending should influence a firm primarily through its choice of maximum capacity as shown in equation 2.4, which might not be binding at lower realizations of demand. Similar applications of quantile regressions include the

work of Arellano et al. (2017) to estimate household income and savings processes with panel data.

Equations 2.6 and 2.7 form a system of credit demand. It is represented through the *marginal* propensity in each retailer-quarter to withdraw a bank or platform loan respectively. Platform borrowing b^1 may occur whenever an online loan offer is extended; its characteristics including the interest rate, maximum maturity and principal provide controls for the propensity of retailer loan withdrawal. Bank borrowing will be assumed to be always available, although the characteristics of the choices facing retailers are not readily observed in the data; in practice, a potential borrower's credit bureau score is correlated with bank loan frequency and size and will be used as a control. A prominent feature of the joint distribution of borrowing choices in this dataset is that a significant fraction of loans is issued simultaneously from both banks and platform to a single retailer, as shown in table 3.4. This specification allows for this, as well as a more conventional discrete choice model as a special case.

The random variables u_Y, u_0 and u_1 describe the uncertainty in this model. They are uniformly distributed in the [0,1] interval, indicate the realization of revenue y_{it} as the draw of a quantile by selecting the random coefficients $\beta_t(\tau)$ for each possible quantile rank $\tau \in [0, 1]$, and generate borrowing by checking u_0 and u_1 against their respective propensity score thresholds P_t. Their joint distribution captures the latent correlations in this specification, which in terms of the inventory model in section 3 may represent the influence of hidden shocks to retailer markups, demand, working assets, or fixed costs on sales and borrowing choices. By Sklar's theorem, the likelihood of a triplet (y, b^0, b^1) can be represented without loss of generality in terms of marginal likelihoods and a copula density function (with conditioning omitted for notational convenience):

$$f(y, b^0, b^1) = f(y) \cdot f(b^0) \cdot f(b^1) \cdot c(F(y), F(b^0), F(b^1)) \tag{2.8}$$

The structure I assume for the joint distribution of these three variables draws from the graphical model of Bedford and Cooke (2002), which represents the copula density above as a *vine of pair-copula densities*. As a preliminary step, the entire likelihood can be factorised as:

$$f(y, b^0, b^1) = f(y) \cdot f(b^0|y) \cdot f(b^1|b^0, y) \tag{2.9}$$

The simplifying assumption of a vine copula model consists of expressing the conditional densities in equation 2.9 as the product of a pair-copula density and another conditional density of lower dimension. That is, for a d-dimensional vector $\boldsymbol{v}$, its j-th component can be extracted as[25]:

$$f(x|\boldsymbol{v}) = c_{xv_j|\boldsymbol{v}_{-j}}(F(x|\boldsymbol{v}_{-j}), F(v_j|\boldsymbol{v}_{-j}))f(x|\boldsymbol{v}_{-j}) \tag{2.10}$$

With this assumption, every conditional density in equation 2.9 can be iteratively reduced to the product of a marginal likelihood and several pair-copula densities. This structure will be used to estimate the joint distribution of revenue and borrowing choices under two menus in any given period: those which include a platform loan offer, metonymically referred to as menu 1, and those which do not. The expression for a copula density $c(u_Y, u_0, u_1)$[26] and the parameters governing latent correlations in each menu are detailed in figures 2.9 and 2.10: in each of the graphs, vertices denote endogenous variables and edges indicate the existence of a pair-copula modeling a correlation between them, whose magnitude maps to the parameter above the edge.

[25]The notation for pair-copula densities mirrors that of Aas et al. (2009)

[26]Where $u_Y = F^{-1}(y)$ rescales a draw of y to its quantile rank, just as for u_0, u_1.

Figure 2.9: Menu 0 vine copula

$$c^0(u_Y, u_0) = c^0_{Y0}(u_Y, u_0; \rho^0_{Y0})$$

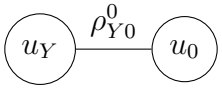
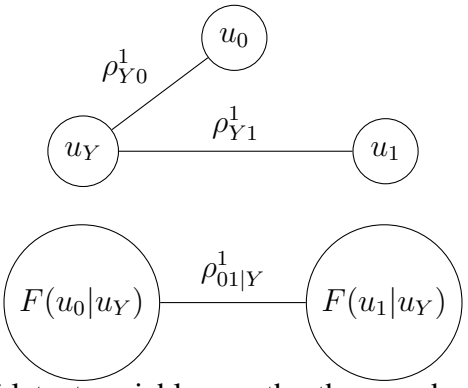


Figure 2.10: Menu 1 vine copula

$$c^1(u_Y, u_0, u_1) = c^1_{Y0}(u_Y, u_0; \rho^1_{Y0}) \cdot c^1_{Y1}(u_Y, u_1; \rho^1_{Y1}) \cdot c^1_{01|Y}(F(u_0|u_Y), F(u_1|u_Y); \rho^1_{01|Y})$$



These two distributions represent the influence of latent variables on the three endogenous outcomes. The inventory model in section 3 does not provide a complex framework to analyze the choice of loan by a retailer when multiple options are available. Since loans are fixed to a short maturity of a single period and there are no constraints on borrowed amounts, the retailer should opt for the alternative with the lowest interest rate for all of their working capital needs. However, both the platform itself and small business surveys in other countries[27] highlight the existence in practice of fixed costs of loan origination, which might steer potential borrowers towards particular options, and borrowing (soft) limits, which might make funding from any one source impossible or more expensive as the desired loan increases in size. Their total loan utilization together with observed loan offer characteristics might be informative about a retailer's revenue parameters. The size of the desired loan in the inventory model is determined by the retailer's working capital, markups and demand expectations, all of which may be subject to unobserved variation. The loan's maturity, a characteristic observable in platform loan offers but hidden in bank credit, has

[27]For example, the aforementioned Wiersch et al. (2019) report by a Federal Reserve collaboration in the United States.

also been identified as a source of adverse selection in consumer lending by Hertzberg et al. (2018).

The construction of the empirical model is completed by an expression for realized loan size l_{it} by borrowers from either source, which in the case of platform loans is censored by an observed borrowing limit $\bar{l}_{it}$:

$$l_{it}^0(x_{it}^0, \varepsilon_{it}^0) = p(x_{it}^0)'\gamma_t^0 + \varepsilon_{it}^0$$
$$l_{it}^1(x_{it}^1, \varepsilon_{it}^1) = \max\{p(x_{it}^1)'\gamma_t^1 + \varepsilon_{it}^1, \bar{l}_{it}\}$$

The main challenge to perform inference on loan size parameters is selection bias, since loans are naturally unobserved among non-borrowers. Although Arellano and Bonhomme (2017) have developed an estimator to account for sample selection in a quantile regression framework which introduces latent correlations through a copula, as in this empirical model, my choice of a vine copula is not readily adapted to their algorithm, which simultaneously estimates outcome marginal distributions and copula parameters[28]. For simplicity, I will assume that ε^0, ε^1 are mutually independent (and likewise independent of u_0, u_1 and u_Y), and that ε^1 is normally distributed to employ a Tobit estimator for platform loan size.

2.4.2 Model identification and estimation

A prominent feature of a copula model like the one introduced in the previous section is the separation between the marginal likelihood of a set of random variables and their correlations, shown in equation 2.8. This accommodates latent correlations between mixed-type data, such as discrete borrowing choices and continuous retailer revenue, and motivates a simple algorithm to estimate the parameters of the empirical model, starting with the marginal distributions of the

[28]The identifying equations, however, are similar. Contrast equation 5 in Arellano and Bonhomme (2017) with equations 6 and 7 in Aas et al. (2009), which condition on a continuous variable instead of a discrete one. I will rely on the latter's definition of an h-function extensively in the next section.

endogenous variables and progressing through 'levels' of each vine copula.

The marginal distribution for retailer revenue y_{it} is estimated by standard quantile regression, which benefits from existing fast algorithms[29]. For each quarter in the data, conditional quantiles are estimated for ten evenly spaced points in the $[0, 1]$ interval and then used to approximate the quantile rank of each revenue realization $\hat{u}_{Y,it}$ by performing Akima interpolation over the grid of estimated quantiles $\{p(x_{it}^Y)'\hat{\beta}_t(\tau)\}$, where $\tau \in \{0.05, ..., 0.95\}$[30]. The remaining parameters are estimated by maximum likelihood. I assume a probit model for the marginal propensity to withdraw a loan from either source, which in the case of platform loans then equals $P_{1,t}(x_{it}^1) = \Phi\left(x_{it}^{1\prime}\delta_{1,t}\right)$.

The copula parameters in each menu are identified by the relationship between the joint distribution of subsets of the endogenous variables and their marginal distributions. The sequence of pairwise correlations involved is implied by the order in which the likelihood of equation 2.9 is factorized[31]. The only 'multilevel' vine copula in the empirical model corresponds to menu 1, in which the first level consists of pair-copula distributions including revenue y_{it} and one of the two borrowing indicator variables, b_{it}^0 or b_{it}^1. In the case of the latter, for example, the corresponding pair-copula distribution function is identified by the propensity to withdraw a platform loan, conditional on the contemporaneous realization of revenue:

$$\begin{aligned}\text{Prob}(b_{it}^1 = 1 | y_{it} = q(u_Y|x_{it}^Y), x_{it}^Y, x_{it}^1) &= \text{Prob}(u_1 < P_{1,t}(x_{it}^1)|u_Y, x_{it}^Y, x_{it}^1) \\ &= \frac{\partial C_{Y1}^1(P_{1,t}(x_{it}^1), u_Y; \rho_{Y1}^1)}{\partial u_Y} = h(P_1, u_Y; \rho_{Y1}^1)\end{aligned}$$

[29]Specifically, using the method of moments estimator by Koenker and Bassett (1978), $\beta_t(\tau) = \arg\min_\beta \sum_{i=1}^n \rho_\tau\left(y_{it} - p(x_{it}^Y)'\beta\right)$, where ρ_τ is the *check function* $\rho_t(u) = u(\tau - \mathbf{1}\{u < 0\})$

[30]This results in extrapolation for values of y_{it} below the 5th and above the 95th percentile. Other possible approaches, like the one used in Arellano et al. (2017), provide unbounded support for y by assuming an exponential distribution below the first and above the last quantiles in the grid.

[31]The vine in figure 2.10 corresponds to a *canonical vine* (or C-vine) copula with revenue quantile ranks u_Y at the root

The parameter governing this relationship, ρ^1_{Y1}, is estimated by maximum likelihood after imputing a quantile rank of revenue $\hat{u}_{Y,it}$ and marginal propensities to borrow $\hat{P}_{1,it}$ based on the quantile regression and probit models described previously. I assume that the functional form of every pair-copula in this model corresponds to a Frank copula[32].

The second level of the vine copula incorporates all endogenous variables and is identified by the joint distribution of b^0_{it} and b^1_{it} after conditioning on y_{it}, as reflected in the choice probabilities below:

$$\text{Prob}(b^0_{it}=1, b^1_{it}=1|u_Y, x^Y_{it}, x^0_{it}, x^1_{it}) = C^1_{01|Y}(h(P_0, u_Y; \rho^1_{Y0}), h(P_1, u_Y; \rho^1_{Y1}); \rho^1_{01|Y})$$
$$\text{Prob}(b^0_{it}=0, b^1_{it}=0|u_Y, x^Y_{it}, x^0_{it}, x^1_{it}) = 1 - h(P_0, u_Y; \rho^1_{Y0}) - h(P_1, u_Y; \rho^1_{Y1}) + C^1_{01|Y}(.)$$
$$\text{Prob}(b^0_{it}=1, b^1_{it}=0|u_Y, x^Y_{it}, x^0_{it}, x^1_{it}) = h(P_0, u_Y; \rho^1_{Y0}) - C^1_{01|Y}(.)$$
$$\text{Prob}(b^0_{it}=0, b^1_{it}=1|u_Y, x^Y_{it}, x^0_{it}, x^1_{it}) = h(P_1, u_Y; \rho^1_{Y1}) - C^1_{01|Y}(.)$$

The distribution of the latent variables u_0, u_1 and u_Y provides a flexible discrete choice system that accommodates simultaneous borrowing, such as occurs in the data as documented in table 3.4. Two extreme cases assist in the interpretation of the choice probabilities above. As $\rho^1_{01|Y}$ tends to $-\infty$, $C^1(u, v; \rho^1_{01|Y})$ converges to 0 for all values of u, v such that $u + v \leq 1$, which is consistent with extreme value discrete choice models where the retailer may choose at most one of the borrowing options; on the contrary, as $\rho^1_{01|Y}$ tends to $+\infty$, $C^1(u, v; \rho^1_{01|Y})$ converges to $\min\{u, v\}$, which may be interpreted as a retailer sequentially accepting strictly ranked borrowing

[32]Some desirable properties of the Frank copula are its symmetry and *comprehension*: Frank copulae can produce implied rank correlations for all values between the Fréchet-Hoeffding bounds for different values of $\rho \in \mathbb{R} \setminus \{0\}$. Its copula distribution function is $C(u, v; \rho) = -\rho^{-1} \log\left(1 + \frac{(e^{-\rho u}-1)(e^{-\rho v}-1)}{e^{-\rho}-1}\right)$

options as a random desired loan size increases[33].

Inference on the correlation parameters of the empirical model is performed by subsampling, following the methodology of Chernozhukov and Fernández-Val (2005)[34]. Algorithm 1, proposed by Aas et al. (2009) and specified to this empirical model, explains how to simulate draws of all the endogenous variables, which is useful for two purposes. The first one is to generate a conditional distribution of revenue for retailers with endogenous self-selection into borrowing or otherwise[35], and comparing those distributions for different values of the observed covariates to the predictions of the inventory model in section 3. I will also employ this algorithm to simulate the endogenous variables in the counterfactual analysis included in the next section.

Algorithm 1 Simulate draws of $y_{it}, b^0_{it}, b^1_{it}$ from a menu 1 vine copula

for $m \in \{1, ..., M\}$ **do**
  for $i \in \{1, ..., n\}$ **do**
    Draw w_Y, w_0, w_1 iid $U[0,1]$
    Set $\mathbf{u_Y} = w_Y$
    Set $\mathbf{u_0} = h^{-1}(w_0, u_Y; \rho^1_{Y0})$
    Set $v_0 = h(u_0, u_Y; \rho^1_{Y0})$
    Set $\mathbf{u_1} = h^{-1}\left(h^{-1}(w_1, v_0; \rho^1_{01|Y}), u_Y; \rho^1_{Y1}\right)$
    Set $b^0_{it,(m)} = \mathbf{1}\{u_0 \leq P_{0,t}(x^0_{it})\}$
    Set $b^1_{it,(m)} = \mathbf{1}\{u_1 \leq P_{1,t}(x^1_{it})\}$
    Set $y_{it,(m)} = p\left(x^Y_{it}, l^0_{it,(m)}, l^1_{it,(m)}\right)' \beta_t(u_Y)$
  end for
end for

2.4.3 Results

The first set of results covers the latent correlations between retailer revenue and borrowing choices, with estimates of vine copula parameters for each quarter provided in table 2.4. The most

[33]These cases correspond to the Fréchet-Hoeffding lower and upper bounds, which in the bivariate case are proper copulas with a Kendall's τ rank correlation of -1 and 1 respectively

[34]Although slightly modified to subsampling by blocks, selecting retailers from the panel instead of individual observations

[35]An analogous procedure is used, for example, in Mata and Machado (2005). In this case, I simulate $M = 20$ draws of $y_{it}, b^0_{it}, b^1_{it}$ for each retailer-quarter in the data.

significant relationship occurs between bank and platform borrowing, with an average Kendall's τ rank correlation of 0.07 over all quarters. To provide an interpretation based on a retailer with a marginal propensity to withdraw a loan from either source of 0.2 (the average propensity among high-risk retailers shown in table 3.4), comparing a non-borrower and a borrower from any one source yield conditional probabilities to withdraw a loan from the other of 0.19 and 0.23 respectively[36]. A possible determinant of this result, supported by the observation that 56% of platform loans are issued at the borrowing limit associated to the corresponding offer, is that isolated borrowing alternatives might be insufficient to satisfy retailers' working capital demand. However, available data do not allow an immediate comparison of platform and bank credit characteristics or even confirmation that the latter exist as an alternative, particularly for high-risk unincorporated retailers.

Estimates of latent correlations between borrowing decisions and contemporaneous retailer revenue distinguish bank from platform loans, regardless of whether the latter are available. While there is little evidence of a significant correlation between bank loan withdrawal and revenue, the coefficients for all but two quarters indicate that the acceptance of a platform loan is correlated with higher retailer revenue[37], and this relationship is significant at the 0.05 level in quarters 4 and 5.

Figure 2.11 compares three quantiles of the distribution of revenue in quarter 4 for retailers blocked according to their revenue in the previous quarter. The mean revenue difference between borrowers and non-borrowers is 6.3% and this difference increases to 10.8% for retailers below quarter 3 median revenue; moreover, this difference is maintained across several quantiles of the conditional revenue distribution. This suggests that retailer controls other than size, including re-

[36]For the average low-risk retailer from table 3.4, the marginal propensity to borrow is 0.27 for bank loans and 0.11 for platform loans. In this case, the conditional probability of bank loan take-up conditional on the acceptance of a platform loan offer is 0.32, and 0.26 conditional on rejection. Reversing the conditioning variables yields a probability of platform loan acceptance of 0.13 in quarters with a bank loan, and 0.10 otherwise

[37]Observe that a loan occurs whenever u_1 lies below the threshold $P_{1,t}(x^1_{it})$

Table 2.4: Vine copula correlation parameter estimates by quarter

	ρ^0_{0Y}	ρ^1_{0Y}	ρ^1_{1Y}	$\rho^1_{01\|Y}$
$t=1$	0.38	-0.04	-0.27	0.67
	(0.05, 0.64)	(-0.36, 0.30)	(-0.49, 0.08)	(0.13, 1.30)
$t=2$	-0.02	0.16	-0.14	0.29
	(-0.34, 0.21)	(-0.13, 0.46)	(-0.37, 0.06)	(-0.01, 0.78)
$t=3$	0.20	0.11	0.00	0.36
	(0.01, 0.42)	(-0.16, 0.42)	(-0.24, 0.25)	(0.06, 0.84)
$t=4$	-0.04	-0.08	-0.38	0.50
	(-0.32, 0.17)	(-0.34, 0.17)	(-0.68,-0.17)	(0.08, 1.00)
$t=5$	-0.17	0.12	-0.48	0.82
	(-0.38, 0.03)	(-0.13, 0.36)	(-0.70,-0.21)	(0.40, 1.31)
$t=6$	0.13	0.02	-0.20	0.95
	(-0.10, 0.30)	(-0.21, 0.31)	(-0.46, 0.11)	(0.48, 1.46)
$t=7$	0.26	-0.08	-0.05	0.56
	(-1.89, 1.77)	(-0.74, 0.83)	(-0.34, 0.17)	(0.06, 2.37)
$t=8$	0.07	-0.09	0.03	0.55
	(-0.19, 4.16)	(-0.33, 0.14)	(-0.23, 0.31)	(0.13, 1.05)

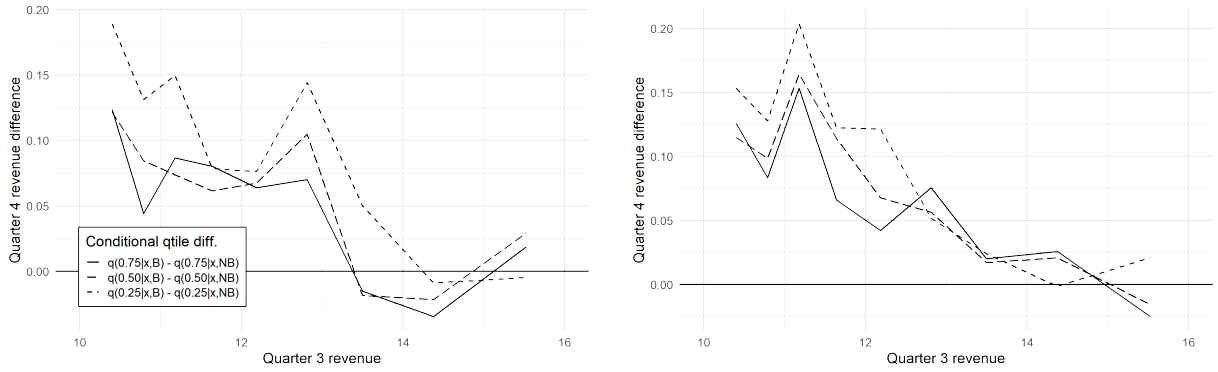
Notes: Estimates of all ρ parameters corresponding to each pair-copula in figures 2.9 and 2.10. 95% confidence intervals estimated by subsampling, with 400 subsamples of size 4000.

tailer category and incorporation indicators as well as the platform's sales forecast, as well as latent variation across retailers, form an environment of advantageous selection by retailers into platform credit withdrawal[38]. The absence of this difference among large businesses may be attributed to disparate factors, such as better collection of otherwise retailer-privy information among the variables highlighted by the inventory model, or the diminished relevance of platform loans among the largest retailers, where loan size caps might deprive these firms of the working capital they require to service positive demand shocks.

2.5 Counterfactual Analysis

The model in the preceding section provides a framework to analyze a retailer's outcomes in the presence of endogenous borrowing, where loans originate from menus that may or may not include

[38]Contrast figure 2.11 with the corresponding figure 2.8 generated from the inventory model.



(a) Low credit score

(b) High credit score

Figure 2.11: Difference between borrower and non-borrower revenue distributions

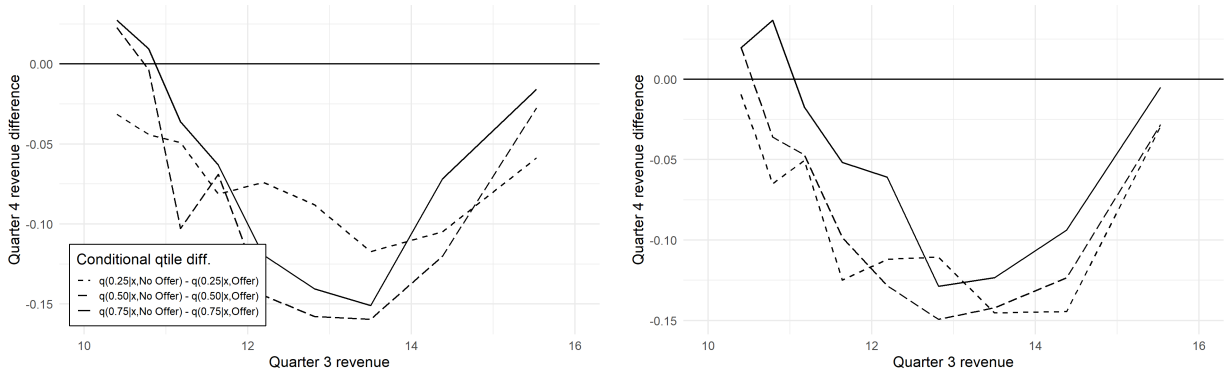
Notes: Difference between the distribution of borrower and non-borrower quarter 4 (2018 Q2) revenue, assessed at four quantiles and conditional on blocks of retailer size, defined as revenue in the previous quarter measured in log ARS, and divided between low and high-credit score borrowers using the same criterion as in table 3.4. Each point in the graph corresponds to one block, consisting of one decile of quarter 3 revenue. Quantiles are estimated based on simulation of the vine copula model for menu 1, performed $M = 20$ times for each retailer. Borrowers correspond to retailers who accept either a bank or a platform loan in quarter 4. For reference, the median firm in quarter 3 has a log revenue of 14.00 (equivalent to 60100 USD), and the median individual retailer 11.25 (3860 USD).

a platform loan offer. A counterfactual exercise that illustrates the option value of a platform loan in a similar vein to the analysis of section 2.4 is to simulate the behavior of retailers when any loan offers from the platform are removed. In the empirical model, a short-term counterfactual is achieved by simulating draws from the menu 0 vine copula for any retailer that had received a platform offer in a given quarter.

The supporting assumption for this analysis is that the platform's offer recipients are selected on observable characteristics of the retailer and thus uncorrelated with u_0, u_1 or u_Y. While the empirical model accounts for latent correlations between firm choices and outcomes, this counterfactual involves some extrapolation based on retailer characteristics. The most significant one is based on accumulated platform debt: while only 17.2% of offer recipients are liable for a past loan accepted from the platform, this number increases to 39.8% of offer non-recipients. To address this, the counterfactual is performed for all offer recipients as well as only the recipients

who hold some debt at the beginning of a quarter[39].

The results of this exercise in the fourth quarter are displayed in figures 2.12 and 2.13. A comparison between 20 simulations for each retailer results in an average revenue decrease of 3.5% (6.0% for refinancers) when the platform's offer is removed, in the same quarter where it would have been received. This effect is larger in magnitude among middle-sized retailers, and clustered around the median size of an incorporated retailer in the previous quarter. These estimates stand in contrast with the estimated short-term treatment effect of 16% from receiving a platform offer reported in table 2.3, although both effects are proportional to the capital allocated by the platform through its loans. In the sample of first-time offer recipients used to estimate the reduced-form in section 2.4, total loans amounted to 12% of revenue in the treated group, relative to a value of 3.6% for the same statistic among all offer recipients, over which the counterfactual was evaluated. This is consistent with the observation that first-time recipients are potentially riskier, marginal retailers with a higher return to lending in terms of revenue growth.



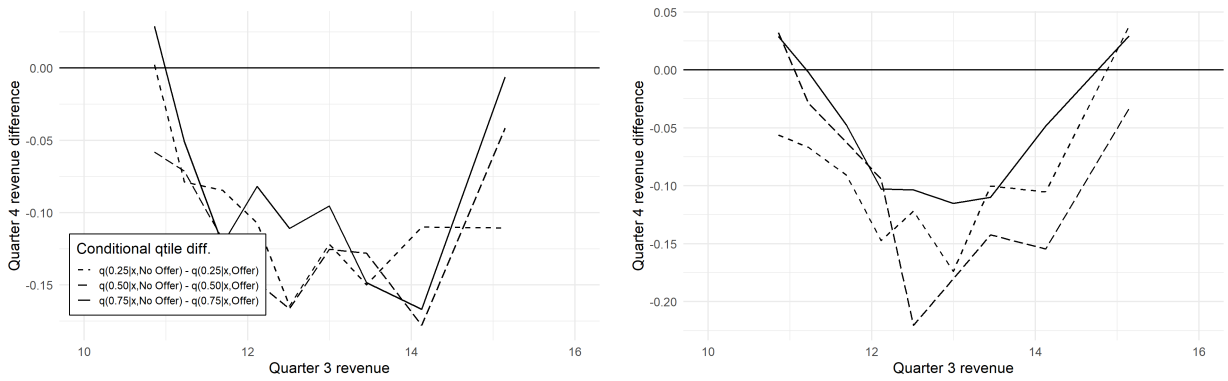
(a) Low credit score

(b) High credit score

Figure 2.12: Simulated distributions, with and without platform borrowing option

Notes: Difference between the distribution of quarter 4 (2018 Q2) revenue for retailers who received a platform loan offer, based on the simulation of a counterfactual menu 0 ('No offer') and the real menu 1 ('Offer') vine copula. Distributions assessed at four quantiles and conditional on blocks of retailer size, defined as revenue in the previous quarter. Each point in the graph corresponds to one block, consisting of one decile of quarter 3 revenue. Simulation performed 20 times for each retailer-menu combination.

[39]I describe the latter as *refinancers*, although the term is not fully appropriate since the characteristics of one loan are not changed when another offer is accepted.



(a) Low credit score

(b) High credit score

Figure 2.13: Simulated distributions, with and without platform borrowing option, refinancers

Notes: Same as figure 2.12, but limited to retailers with positive liabilities owed to the platform at the beginning of the fourth quarter.

2.6 Concluding remarks

This article documents how an e-commerce marketplace has introduced online lending services to a population of small retailers, connected to it through online sales or payment processing, at a scale comparable to the entire commercial banking sector of Argentina's penetration in the same market[40]. Reduced-form analysis, complemented by a novel model of latent heterogeneity underlying retailer credit and revenue outcomes, reveals a significant impact on retailers recently inducted into its automated lending program as well as the average business in my sample, in both cases potentially multiplying revenue by a factor above unity relative to allocated capital. These rates of return on external funding, in addition to the finding of positive latent correlation in the usage of multiple credit sources, suggest that credit constraints remain a significant obstacle to the sustained growth of small retail businesses.

Future research in this area can benefit significantly from improved marketplace data collection. In recent years and in similar fashion to other e-commerce giants, the marketplace I study incorporated fulfillment to the menu of services offered to its retailers. This provides the platform with an opportunity to observe a merchant's inventory decisions as well as the consequences of a

[40]This refers to the final statistics mentioned in section 2.1

mismatch between inventory and demand, such as lost or delayed sales and costly storage of unsold goods. Coupled with online marketplace variables that can inform estimation of downstream demand for shipped goods, this would enable a structural estimation of inventory models like the one introduced in section 3 on a large population of businesses. This approach can be integrated into the literature of production function estimation with potential resource misallocation as a more specific and detailed application to the problems studied by Lenzu and Manaresi (2019) and Cao and Leung (2020).

Thorough understanding of a retailer's input demand behavior in the context of liquidity constraints serves as a starting point to analyze incentives to lend that might be unique to e-commerce platforms which expand to provide financial intermediation. This category currently includes some of the largest firms in existence, such as Amazon and Ant Group, and constitutes a novel setting where the objective of a platform may be akin to that of a supplier providing trade credit to downstream merchants, but the instrument to fulfill this objective in turn resembles a lending product from the financial sector, deployed at a massive scale through novel algorithms. These products might serve to lower entry barriers and facilitate long-term growth in a sales platform that is more resilient to macroeconomic shocks than traditional retail at a cost of external funds to businesses that a competitive banking sector could not match, as concluded by Kouvelis and Zhao (2012). However, other economists such as Barrot (2016) contend that trade credit practices might result in imperfect risk sharing and the propagation of barriers to entry and competition to other links of the supply chain.

Chapter 3

Online Lending Facilitates SME Credit Building[1]

3.1 Introduction

Small and medium-sized enterprises (SMEs) are frequently constrained by limited access to external financing, which manifests in the form of high interest rates or credit rationing (Wiersch et al., 2019) and impacts their growth and the ability to withstand various economic shocks (Cao and Leung, 2020). Some factors that hamper the formation of long-term contracts between lenders and SMEs include a high cost of origination and enforcement relative to small loan amounts, which in turn compounds the inherent risk of dealing with small firms with high exit rates (Petersen and Rajan, 1994). In extreme cases, these contracting frictions result in the unraveling of credit markets, producing a population of *invisible* (Burke et al., 2019) agents with almost nonexistent credit records.

In the last decade, advances in financial technology have provided numerous alternatives to traditional bank or credit unions as sources of lending and introduced novel mechanisms to

[1]I am grateful to managers and staff from the lending platform for providing data and informing my understanding of their products.

monitor and enforce these contracts (Branzoli and Supino, 2020). Many of these *fintech* products originate from firms completely specialized in online intermediation or non-financial suppliers that bundle *fintech* lending with other goods and services, which leaves both outside the purview of preexisting financial regulation. This article, a companion paper to Baratuche (2021), focuses on the latter as I study a major South American e-commerce marketplace which offered online loans to merchants operating on its platforms in Argentina starting in 2016. A majority of these merchants are unincorporated small businesses, many of whom have scarce or nonexistent credit records prior to this platform's entry into lending.

E-commerce marketplaces that provide financial services benefit from an integrated approach that enables them to mix traditional credit records on prospective borrowers with alternative, proprietary databases; process them into credit evaluations through novel algorithms; automatically engage in large-scale loan origination; and enforce loan repayment through the same platforms on which retailers may earn most of their revenue (Frost et al., 2019; Hau et al., 2021). In addition, these loan products are offered together with financial services such as payment processing and other forms of retail intermediation that combine into a relevant bundle of products for online retailers, which in turn may lower the merchant-facing cost of loan origination relative to applying separately at a bank.

As a result of these comparative advantages, several big tech companies have successfully extended small business lending to market segments with little prior bank penetration, with examples including South America (Baratuche, 2021; Frost et al., 2019) and China (Hau et al., 2021). This increased credit supply has been harnessed by many retailers resulting in sustained revenue growth and, at least in the aforementioned case of Argentina, loan defaults have remained below average commercial default rates. However, banking regulators are concerned that other potential lenders are limited in their ability to compete in these new markets (Feyen et al., 2021). One channel that might enable the entry of other financial suppliers is the *spillover* of information

on the creditworthiness of small businesses that are inducted into big tech lending programs, since repayment is typically monitored by credit rating agencies.

The objective of this article is to quantify the extent to which big tech entry into credit markets facilitates information to the rest of the financial sector through this channel. I analyze a panel of retailers provided by an e-commerce marketplace which developed an algorithm to decide which businesses to offer loans to and under what terms. The panel includes key retailer characteristics such as credit bureau scores, accessible by both this marketplace and other financial institutions, as well as a marketplace-exclusive credit assessment which is used as an input for the lending algorithm. This allows me to control for the platform's credit supply before observing retailers' decision to borrow or not from any lending sources available to them over time. Variation over time of the availability of marketplace loans to this population of retailers identifies the causal effect on various outcomes of interest, such as bank-facing credit scores and usage of third-party loans, which is estimated through a similar methodology to that used by Baratuche (2021).

The first result I discuss is an average estimated increase of credit scores following the marketplace's entry as a borrowing alternative. To the extent that this effect is mediated by credit usage rather than its availability, I use online loan offers as an instrumental variable for borrowing take-up and find that among retailers with below-median creditworthiness their credit score increases by a full quartile of the unconditional distribution. This complements findings such as those by Karlan and Zinman (2009), which argue that credit-building products tend to have a mixed effect depending on the underlying fundamentals of borrowers which use them as a signalling opportunity. However, since loan offer recipients are carefully curated by the marketplace's lending algorithm, the prevailing selection effect might be the lender's instead of any self-selection on behalf of the borrowers.

The second result is an estimated increase in retailer bank borrowing following the marketplace's entry decision. While Baratuche (2021) highlights that retailer self-selection might render bank and online borrowing decisions positively correlated with each other, the estimated increase in bank credit demand following online loan take-up is four times as large as the self-selection bias found in the cited article. This effect is likely mediated by improved borrowing opportunities through standard loans once retailers signal their creditworthiness through online loan repayment, but estimates are missing of possible countervailing effects such as the substitution between online and bank loans.

3.2 Data

The data used for this analysis is a subsample of the dataset employed by Baratuche (2021), which consists of a quarterly panel of merchants operating on one of the data provider's platforms[1] between May 2017 and May 2019. The dataset includes merchant characteristics generated by third parties, specifically a credit score compiled by a major local credit bureau and records of merchant debt owed to local banks, disaggregated by repayment status, and other variables gathered by the platform itself which include retailer revenue and a proprietary score designed to predict future sales performance. These variables are collectively employed by the platform to generate a stream of online loan offers, each consisting of an interest rate, maximum principal and maturity, all of which are observed together with retailers' response to withdraw a loan or not.

The subsample I study is designed according to the criteria outlined in section 2.4 of Baratuche (2021), which selects merchants who are first considered by the platform for a *potential* loan offer in the first half of the panel and with a credit bureau score below the whole-sample median of 477. The reason for this is that, while these high-risk merchants borrow at a frequency comparable

[1] This includes an online e-commerce marketplace, as well as offline sales handled at the point of sale through this company's payment processing service.

to low-risk agents[2], the former's loans are primarily supplied through online loans originated by the data provider, whereas the latter resort mainly to traditional bank loans. This indicates that high-risk retailers might be constrained in their usage of bank loans while maintaining a demand that the lending platform can fulfill through their own services; selecting only retailers who have received a preliminary evaluation ensures that none of the variables of the preceding paragraph are missing and that I can control for them in the analysis[3].

Table 3.1: Summary Statistics

	N_{obs}	Mean	St. Dev.	$P_{25\%}$	$P_{50\%}$	$P_{75\%}$
Retail characteristics						
Sales volume	21,505	19,169	116,591	791	2,067	6,957
Marketplace share	21,505	0.59	0.44	0.00	0.85	1.00
Public credit characteristics						
Bank debt	21,505	20,091	869,296	0	254	1,992
Share of debt distressed[1]	13,159	0.11	0.30	0.00	0.00	0.00
Bureau score	21,505	313	179	204	340	445
Platform credit characteristics						
Offer size	10,003	11,883	33,944	519	1,489	6,207
Loan size	2,184	3,464	9,145	396	866	2,489
Maturity (months)	2,184	8.5	3.5	6	9	12
Interest rate (p.p.)	2,184	71.68	22.54	56.00	66.00	88.50

Notes: Retailer characteristics by quarter. Monetary values are reported in current USD. Sales are observed for every retailer-quarter; share of distressed debt is reported for each retailer-quarter with positive liabilities; the lender's offer size is quoted for each retailer-quarter with at least one platform loan offer; maturity and interest rate correspond to each accepted platform loan offer.

[1] Debt stock is classified as distressed if it is over 90 days due (*situación 3* or higher as reported in the BCRA *Central de Deudores)*

Summary statistics are provided in table 3.1. The retailers selected for this analysis are smaller than those representing the overall sample[4], although the online platform tends to extend these merchants larger offers relative to their sales volume. Loans in this subsample are originated at an average lower maturity, and over all quartiles of their respective distributions a single online loan

[2] See table 2 of Baratuche (2021)

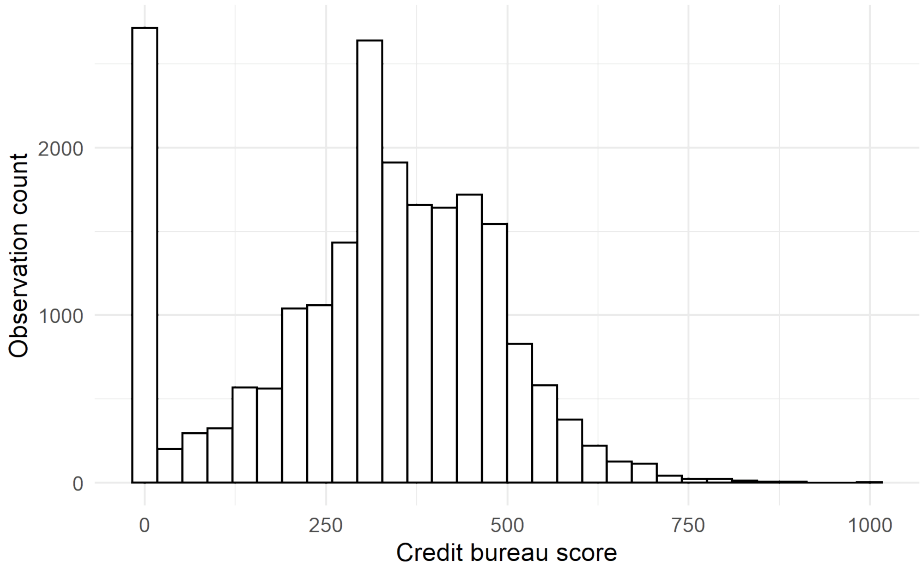
[3] A discussion of how this preliminary evaluation is conducted is outlined in the next section.

[4] Compare with table 1 in the cited article

exceeds the total amount of debt that merchants accumulate with all banks in any given quarter. In particular, nearly a third of retailer-quarters feature no bank debt at all on record.

Figure 3.1 shows the distribution of credit bureau scores in this subsample and sheds some light on the composition of high-risk retailers. Notably, 12.3% of observations are concentrated at the minimum possible value, which roughly correspond to active or recent default events - for reference, 8.2% of retailer-quarters in this sample feature bank debt more than 90 days overdue, which is commonly processed as a default indicator. While the data provider codes defaults differently, they affect 3.7% of online loans in this sample.

Figure 3.1: Credit bureau score distribution



Notes: Distribution of credit bureau scores for the sub-sample of retailer-quarters analyzed in section 3. Featured retailers must have been first assessed by the platform in the *first half* of the selected periods and possessed an initial credit score below the whole-sample median of 477.

3.3 Empirical model

In this section I measure how the online lender's entry affects the *availability* and *usage* of other borrowing options to merchants, which in this context would originate primarily from the banking sector. The main channel that affects bank loan supply is information that successful repayment of online loans provides to other prospective lenders; offsetting effects may include the fact that default events are more common when borrowers engage in multiple non-exclusive loan contracts as documented by De Giorgi et al. (2017), thus raising the cost and risk of lending to this population.

The foremost challenge I address when estimating the causal effect of a lender's entry decision is the existence of selection bias generated by the credit supplier's choice of which businesses to engage with loan offers; in contrast, Baratuche (2021) focuses on quantifying the self-selection induced by the merchants' take-up of these offers. For both of the outcomes I analyze, the identification of these effects relies on controlling for the selection of loan offer recipients with observable merchant characteristics. The data provider proceeds by algorithmically evaluating retailers and progressively gathering information on prospective borrowers before deciding whether or not to extend an initial credit offer, which is the event that I code as the lender's entry. Pre-selecting retailers who have a complete suite of variables observed in my dataset ensures that I compare retailers treated with this initial offer to a similar control group, as any remaining differences are accounted for by these measurements [5].

3.3.1 The impact of online lending on credit building

The first outcome that I analyze is the evolution of creditworthiness for retailers who are exposed to the initial online loan offer. When accepted, this credit materializes as an installment loan with monthly repayments that are automatically deducted from retailer balances in one of the platforms

[5] Baratuche (2021) describes this evaluation algorithm and its output in more detail.

supported by the lender. All the specifications in table 3.2 correspond to estimates of a two-way fixed effects (for retailer and quarter) regression with current credit scores as the dependent variable and nonparametric controls for specific inputs to the platform's lending algorithm including proprietary scores, firm age and size. In specification (1), a retailer is coded as treated immediately after receiving the first offer by the online lender, regardless of whether it is accepted or not. Since most information that would be reflected in a credit record stems from the acceptance and repayment of this offer, specification (1) can be interpreted as an estimate of the intent-to-treat (ITT) a merchant with additional credit. Specification (2) codes a treated retailer as one who has accepted an online loan, the resulting effect is estimated employing loan offers by the platform as an instrumental variable for actual loans in a similar vein to Angrist et al. (1996). Specification (3) revises the ITT estimate of a loan offer by breaking down the treated state into the amount of quarters passed since an initial treatment date t.

Results indicate an overall increase of credit scores following the entry of the platform as a borrowing option for affected retailers. This effect appears to ramp up over time according to the estimates of specification (3) and is consistent with repayment information being processed as loan installments become due, as well as more loans being generated in the quarters following the initial offer. The estimate of specification (2) indicates a significant average increase following credit take-up, corresponding to a full quartile of the credit score distribution of the entire retailer population studied in Baratuche (2021). This is likely to result from the careful selection of retailers conducted by the lender, in contrast to other credit-building products such as the one studied by Burke et al. (2019) which find a mixed impact of this information generation, partly due to heterogeneity in borrower repayment fundamentals and also due to the stress that new loan trades might impose on their preexisting portfolios.

Table 3.2: Effect of platform entry on retailer credit scores

Variable	(1)	(2)	(3)
Treatment	25	143	
	(3)	(15)	
t			26
			(3)
$t+1$			40
			(3)
$t+2$			46
			(4)
$t+3$			54
			(5)
$t+4$			60
			(5)
N	3427	3427	3427
T	8	8	8
R^2	0.76	0.72	0.76

3.3.2 The impact of online lending on third-party borrowing

The second outcome featured in this study is the usage of third-party loans by merchants in this dataset, which includes the entirety of bank credit originated during this period[6]. The analysis will mirror the one in the previous subsection but with a binary dependent variable capturing the creation of any bank loans in a given retailer-quarter, resulting in a linear probability model.

Specifications in table 3.3 coincide with table 3.2. Regressions (1) and (3) suggest that the availability of online loans increases bank borrowing with a magnitude that ramps up over time, possibly as a result from improved borrowing terms after banks perceive greater creditworthiness among this population. This point is illustrated by table 3.4, which highlights the borrowing rates from bank and online options, in the case that both are available, from the full sample shared

[6]Excluded alternatives include trade credit and any credit secured through personal relationships.

Table 3.3: Effect of platform entry on retailer propensity to borrow from banks

Variable	(1)	(2)	(3)
Treatment	0.028	0.221	
	(0.013)	(0.105)	
t			0.048
			(0.015)
$t+1$			0.060
			(0.017)
$t+2$			0.041
			(0.021)
$t+3$			0.043
			(0.025)
$t+4$			0.089
			(0.029)
N	3427	3427	3427
T	8	8	8
R^2	0.37	0.37	0.38

by the data provider. The interpretation of regression (2) is complicated by the fact that, unlike the case of credit scores which typically only react to loan usage rather than their availability, *assignment to treatment* in the form of an online offer is likely to impact the likelihood of a retailer accepting a bank loan as it provides a competing option[7], resulting in a violation of the exclusion restriction in models of Local Average Treatment Effects. Baratuche (2021) estimates a demand system of retailers who may opt for multiple simultaneous loans with self-selection effects relating the usage of each loan to one another and contemporaneous revenue performance, and provides an estimate of the difference between the probability of bank loan usage, conditional on simultaneous online borrowing and non-borrowing respectively, of up to 5 percentage points to contrast with the estimate in specification (2).

[7]Although online loans tend to be more expensive, as documented by figure 1 in Baratuche (2021), they tend to originate at significantly higher maturities.

Table 3.4: Take-up rate of bank and platform loans

High-risk retailers				Low-risk retailers			
		Platform loan				Platform loan	
		Yes	No			Yes	No
Bank loan	No	15.4%	65.0%	Bank loan	No	7.6%	64.6%
	Yes	5.2%	14.2%		Yes	3.5%	24.0%

Notes: Cross tabulation of platform and bank loan withdrawal rates for retailer-quarters where a platform loan offer is produced. *High-risk retailers* are those with a credit bureau score below the whole-sample median of 477 and *low-risk retailers* the complementary population.

3.4 Concluding remarks

Big tech companies have raised concerns among industry regulators at the same time that they lower the cost of lending in the markets they penetrate. Among new *fintech* providers, they are some of the few entrants with the size required to match incumbents: in the case of the data provider for this article, within three years of launching their product their loan portfolio was worth 75% of all bank loans to unincorporated retailers in the full sample. Their scale and data infrastructure provides them with comparatively lower fixed costs of customer acquisition, while their product mix differs substantially from both traditional lenders and fintech competitors, including core tech services that may be more attractive to borrowing businesses and alter the structure of cross-subsidies spanned by preexisting financial regulation (Feyen et al., 2021).

This article highlights one potential channel by which other lenders can seize on positive externalities originating from online loans. By selectively introducing their product among businesses with adverse or non-existent credit histories, the big tech company I study was able to generate a stream of information that substantially improved the credit record of affected merchants operating on its platforms. While supply and demand forces driving the creation of bank credit are difficult to disentangle in this dataset, borrowing from financial sources *increased* following an online competitor's entry, in contrast to substitution dynamics more frequently occurring in conventional

markets for goods and services.

The entry of even one lender was documented in Baratuche (2021) to facilitate short-run business revenue growth and, while the panel studied is sufficiently short to preclude the observation of more than a couple loans being repaid by a single retailer, the results presented here may hint at the existence of long-run positive effects from the expansion of credit availability. Interesting avenues that would expand the scope of this empirical project could feature a comparison of enforcement power between big tech and other lenders, particularly with an eye to possible externalities in this dimension as modelled by Green and Liu (2021) or De Giorgi et al. (2017), and a breakdown of the various incentives and cross-subsidies of big tech and fintech lenders relative to other financial institutions. Together, these would provide a comprehensive overview of how competition in this industry responds to digital innovation, and illustrate the scope for new or expanded regulation.

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3.5 Chapter 1

Tables

Table 3.5: Naive discrete choice model

	Dependent variable:	
	Cardholders(credit)	Credit card issue
	(1)	(2)
Total access fees	0.002***	0.002***
	(0.0003)	(0.0003)
Overdraft	-2.753e-08	4.927e-08
	(5.235e-08)	(4.913e-08)
Signature credit line	9.791e-09	3.470e-08
	(3.313e-08)	(3.110e-08)
Personal loans	7.122e-08***	6.579e-08***
	(2.032e-08)	(1.907e-08)
Credit card loans	6.140e-08***	5.879e-08***
	(2.015e-08)	(1.891e-08)
Savings deposits	-9.610e-09	-3.676e-09
	(1.424e-08)	(1.336e-08)
	90	
Observations	171	171

Table 3.6: Instrumental variable discrete choice

	Dependent variable:
	Cardholders(credit)
Total access fees	-0.0004
	(0.001)
Overdraft	4.823e-07
	(1.120e-06)
Signature credit line	2.178e-07
	(3.102e-07)
Personal loans	6.930e-08
	(1.562e-07)
Credit card loans	-1.496e-07
	(6.913e-07)
Savings deposits	4.854e-08
	(5.296e-08)
Observations	171
R^2	0.179
Adjusted R^2	0.144
Residual Std. Error	1.724 (df = 163)
BLP IV	91 X
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3.7: Trends and fixed effects on access fees

	Dependent variable:
	log(Total access fee)
month	0.377^{***}
	(0.095)
$\mathbf{1}\{t \geq \text{Apr } 2017\}$	-0.011
	(0.059)
$\mathbf{1}\{\text{Bank owns PRISMA}\}$	0.232^{***}
	(0.039)
PRISMA $\times \mathbf{1}\{t \geq \text{Apr2017}\}$	0.041
	(0.061)
Constant	-754.452^{***}
	(190.945)
Observations	516
R^2	0.204
Adjusted R^2	0.197
Residual Std. Error	0.318 (df = 511)
F Statistic	32.657^{***} (df = 4; 511)
Note:	*p<0.1; **p<0.05; ***p<0.01

Choice of fee structure for an integrated issuer

I want to show an integrated issuer prices transactional services on a marginal cost basis. Its problem in period 1 is:

$$\max_{f_i,F_i}[(m+f_i-c_A-c_I)d(f_i,m)+F_i]Q_i(F_i-\phi(f_i,m),F_{-i}-\phi(f_{-i},m))+$$
$$+\sum_{j\neq i}(m-c_A)d(f_j,m)Q_j(F_j-\phi(f_j,m),F_{-j}-\phi(f_{-j},m))$$

Where $d(f,m)$ is shorthand for transaction volume: $d(f,m) = D_S(m)D_b(f_i)$. First order conditions for this firm are:

$$(f_i):Q_i(.,.)[d(f_i)+d_f(f_i)(m+f_i-c_A-c_I)]-$$
$$\overbrace{Q_{i,1}(.,.)}^{\frac{\partial Q_i(x,y)}{\partial x}}\frac{\partial\phi}{\partial f_i}(f_i,m)[(m+f_i-c_A-c_I)d(f_i,m)+F_i]-$$
$$\sum_{j\neq i}(m-c_A)Q_{j,i}(.,.)\frac{\partial\phi}{\partial f_i}(f_i,m)=0$$
$$(F_i):Q_i(.,.)+Q_{i,1}(.,.)[(m+f_i-c_A-c_I)d(f_i,m)+F_i]+\sum_{j\neq i}(m-c_A)Q_{j,i}(.,.)=0$$

Isolating Q_i from the first order condition for F_i, we get an expression equal to the factor multiplying $\frac{\partial\phi}{\partial f_i}$ in the first order condition for f_i. Therefore, the first equation simplifies to:

$$(f_i):Q_i(.,.)\left(d(f_i)+d_f(f_i)(m+f_i-c_A-c_I)+\frac{\partial\phi}{\partial f_i}(f_i,m)\right)=0$$

$D_S(m)$ drops out from all the terms in the inner sum to produce

$$D_b(f_i) + D_b'(f_i)(m + f_i - c_A - c_I) + \frac{\partial}{\partial f_i}\left(E[b_B - f_i | b_B > f_i] D_b(f_i)\right) = 0$$

$$\begin{aligned}
\frac{\partial}{\partial f_i}\left(E[b_B - f_i | b_B > f_i] D_b(f_i)\right) &= \frac{\partial}{\partial f_i}\left(\int_{f_i}^{\bar{b}_B} (b_B - f_i) g(b_B) db_B\right) \\
&= -\int_{f_i}^{\bar{b}_B} g(b_B) db_B + 0 g(f_i) \\
&= -D_b(f_i)
\end{aligned}$$

Therefore, the FOC for f_i reduces to $m + f_i - c_A - c_I = 0$.

3.6 Chapter 2

Appendix A - Estimation of loan offer propensity scores

The dataset used for this analysis crucially includes many internal variables that the platform employs for the purpose of screening lenders and determining loan offers. However, figure 2.4 highlights that the platform's decision to lend, while indicative of some score-based thresholds, presents only small discontinuities in the probability of issuing an offer relative to Hau et al. (2021)'s study of Ant Group's merchant loans. While the lender did not disclose its offer-issuing algorithm, a few observed variables suffice to explain their lending decisions well. The included variables are:

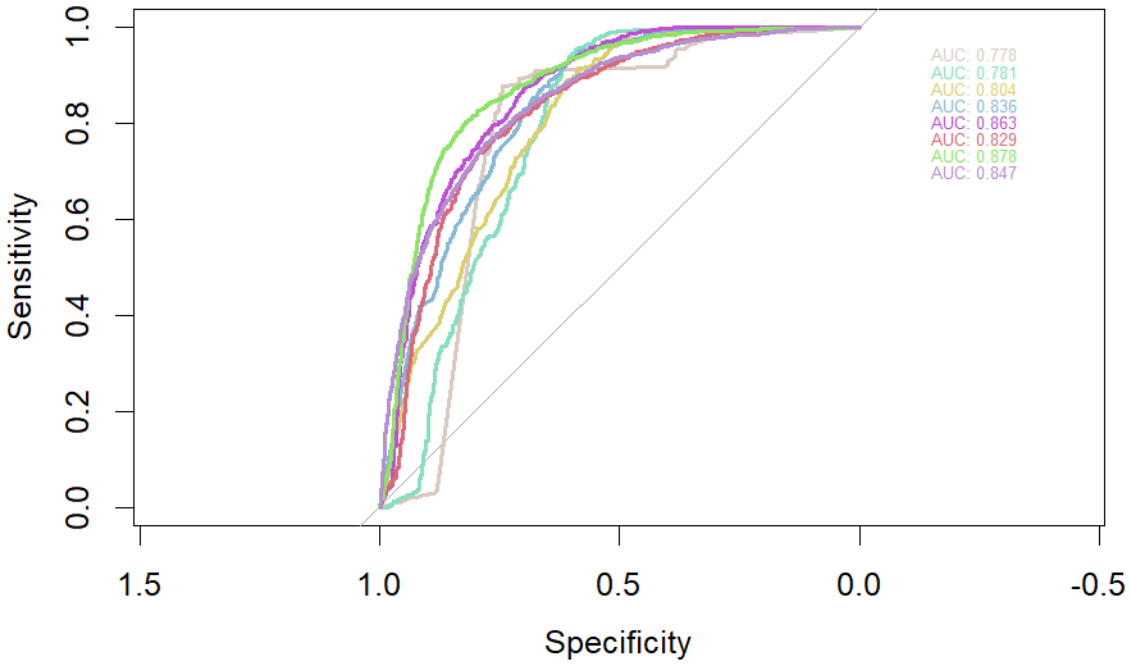
- Retailer sales in the past quarter.
- Internal and credit bureau scores, as displayed in figure 2.4.
- Liabilities owed to platform and bank at the start of the quarter, by risk grade.
- Firm's age in quarters.

In order to accomodate uncertainty about the algorithm's functional form as well as variables that are missing not at random (such as a retailer's platform-facing credit history, which is in many

cases nonexistent as all offers are declined), I estimated the receipt of loan offers in a given quarter with a GBM estimator, the exact implementation of which is documented in Greenwell et al. (2019) for the *R* language. It consists of the original AdaBoost estimator of Freund and Schapire (1997), with subsampling introduced in the gradient descent step as proposed by Friedman (2002). Each step employs a logistic estimator, and model hyperparameters were selected by ten-fold cross-validation over a grid of $\{1, 3, 5\}$ for covariate interaction depth and $\{20, 40, ..., 200\}$ for the number of regression trees. The shrinkage parameter was kept fixed to a low value of 0.1, and minimum subsampling size set to 20.

Estimation was performed separately for each quarter, with goodness-of-fit statistics reported in figure 3.2. Model performance appears to increase over time, which is possibly related to censoring of the age variable at the beginning of the panel induced by the change in the platform's scoring algorithm. While this estimation yields a propensity score for the outcome of receiving a loan offer, these scores were not used in the matching estimator of section 2.4, where I instead opted to use Abadie and Imbens (2006)'s covariate-based matching procedure.

Figure 3.2: Receiver operating characteristic curves and AUC



Notes: ROC curves for the GBM model estimated for each quarter in the panel, with corresponding c-statistics reported chronologically from top to bottom. The low sensitivity reported for the first quarters may owe to firm age being more heavily censored initially (by the start date of the panel relative to initiation of screening by the platform lender).

Appendix B - Derivation of inventory model results

The first-order condition from the problem in section 3 that yields the optimal inventory choice $I^*(k)$ is:

$$p(1-F_i(I)) - c + RcF_i(I) - c\frac{r_B - r}{1+r}\mathbf{1}\{k < A + cI\} + RE_X\left[V'(k'(k,I,x)\frac{\partial k'(k,I,x)}{\partial I}\right] = 0$$

The continuation value of a marginal purchase of inventory is contingent on the realization of random demand, and its expected value (as well as the marginal continuation value of an additional unit of working capital, calculated for a later step) can be expressed in terms of (non-)borrowing indicators $\mathbf{1}\{B\} = \mathbf{1}\{k < A + cI\}$ and $\mathbf{1}\{NB\} = 1 - \mathbf{1}\{B\}$:

$$E_X\left[V'(k'(k,I,x)\frac{\partial k'(k,I,x)}{\partial I}\right] = -c(r_B\mathbf{1}\{B\} + r\mathbf{1}\{NB\})\int_0^I V'(k'(k,I,x))f_i(x)dx+$$
$$(1-F_i(I))V'(k'(k,I,I))(p(1+r) - c(1+r_B\mathbf{1}\{B\} + r\mathbf{1}\{NB\}))$$
$$E_X\left[V'(k'(k,I,x)\frac{\partial k'(k,I,x)}{\partial k}\right] = (1+r_B\mathbf{1}\{B\} + r\mathbf{1}\{NB\})\int_0^I V'(k'(k,I,x))f_i(x)dx+$$
$$(1-F_i(I))V'(k'(k,I,I))(1+r_B\mathbf{1}\{B\} + r\mathbf{1}\{NB\})$$

This establishes a relationship between the marginal value of additional working capital and inventory at I^*:

$$E_X\left[V'(k'(k,I,x)\frac{\partial k'(k,I,x)}{\partial I}\right] = p(1+r)(1-F_i(I))V'(k'(k,I,I)) + c\int_0^I V'(k'(k,I,x))f_i(x)dx-$$
$$cE_X\left[V'(k'(k,I,x)\frac{\partial k'(k,I,x)}{\partial k}\right] \tag{3.1}$$

By an envelope theorem, the marginal value of working capital at state k can be expressed as:

$$V'(k) = \frac{r_B - r}{1+r}\mathbf{1}\{B\} + RE_X\left[V'(k'(k,I,x))\frac{\partial k'(k,I,x)}{\partial k}\right] \tag{3.2}$$

By replacing the expected marginal continuation value of inventory in the first order condition with the expression in equation 3.1, subsequently substituting the marginal value of capital from equation 3.2 yields the reformulated first-order condition 2.2. For sufficiently low values of A_i (and thus a sufficiently low probability that capital $k'(k, I^*, x)$ will be lower than k), this ensures that the optimal inventory choice is lower than both the naïve AHM policy or the inventory policy implied by a one-shot markup of marginal costs by the borrowing interest rate spread due to dynamic effects.