Easing Business Credit Constraints Through Online Lending *

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Abstract. This article studies a major e-commerce platform which introduced an online lending program for affiliated retailers in developing economies. Using data provided by the platform itself, I show that this product quickly became a primary source of funds for targeted small businesses and that the resulting improvement in credit access caused a concurrent increase in retailer revenue of 10 to 25%. I develop a model of information asymmetries between this platform, third-party lenders, and potential borrowers regarding the fundamental characteristics of retailer operations. Estimates indicate that there is positive latent correlation in the usage of online and bank loans and partial evidence of advantageous self-selection by retailers who accept online loan offers. Analysis of a counterfactual withdrawal of the platform's lending product reveals an average increase of retailer revenue greater than its allocation of capital, highlighting the potential of similar platforms to relieve business-facing credit constraints in other settings.

Keywords: SME lending, fintech, firm growth

JEL Codes: D25, G21, O43

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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, Lipman and Lieberman 2019). Virtually issued small business loans, which include direct 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.

[1]A classic overview of the uses of external funding in these functions is Fazzari, Hubbard and Petersen (1988)

[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

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 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 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).

[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.

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

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, Blundell and Bonhomme (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 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 Empirical setting

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 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 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.

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 2 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 (Wiersch, Lipman and Lieberman 2019). This

[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).

informs one of three observations relevant to the rest of my analysis:

Observation 1 *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: 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.

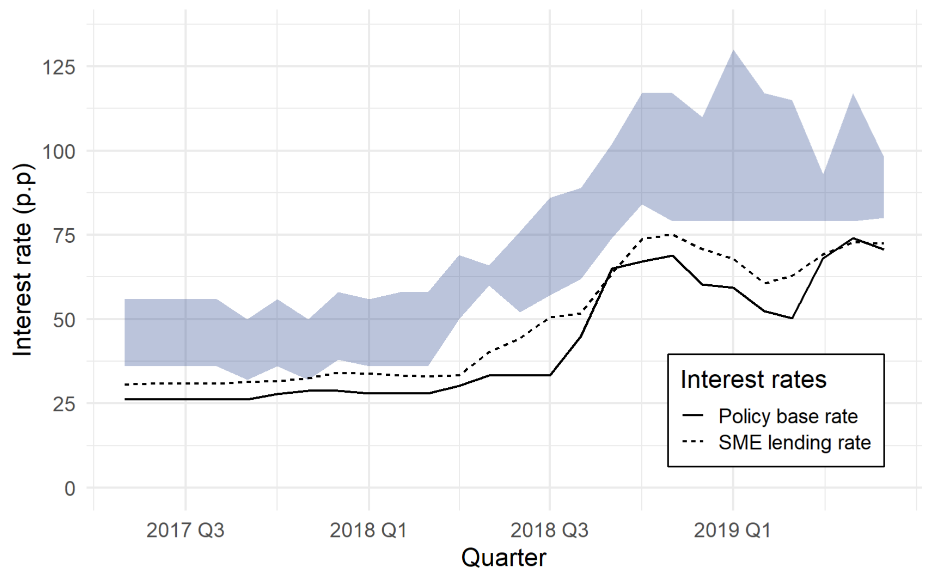
Based on their relatively short maturity of up to a year, the marketplace's merchant loans are working capital loans which stores most commonly employ to restock their inventory between peaks of retail demand. The exact composition of a retailer's bank debt is not included in this dataset, but aggregate 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 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 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

[11]Published as part of the *Cuadros estandarizados de series estadísticas*, under monthly volumes lent to the non-financial private sector.
[12]Called *Ahora 12*, the details of which can be found online at https://www.argentina.gob.ar/ahora-12

accounts payable that a store maintains with upstream suppliers and has a maturity comparable to bank overdrafts.

Figure 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.

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 local financial sector as shown in figure 1. Domestic borrowing experienced a brief increase in 2016 and 2017 but collapsed in the following year as highlighted in figure 2.

[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).

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 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.

Observation 2 *There is a retail cycle, with peaks of revenue spaced at least a quarter apart.*

The marketplace revenue series in figure 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.

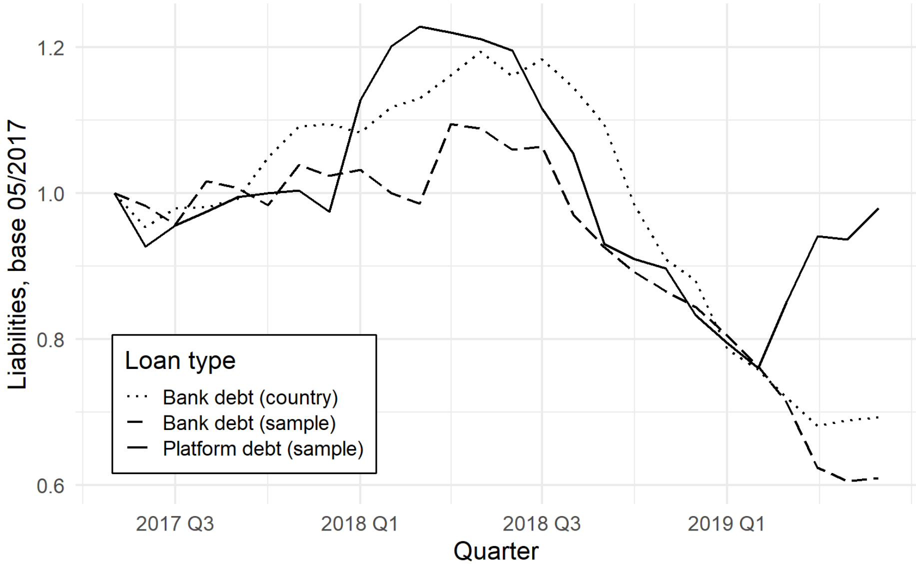
2.3 The platform's lending algorithm

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 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

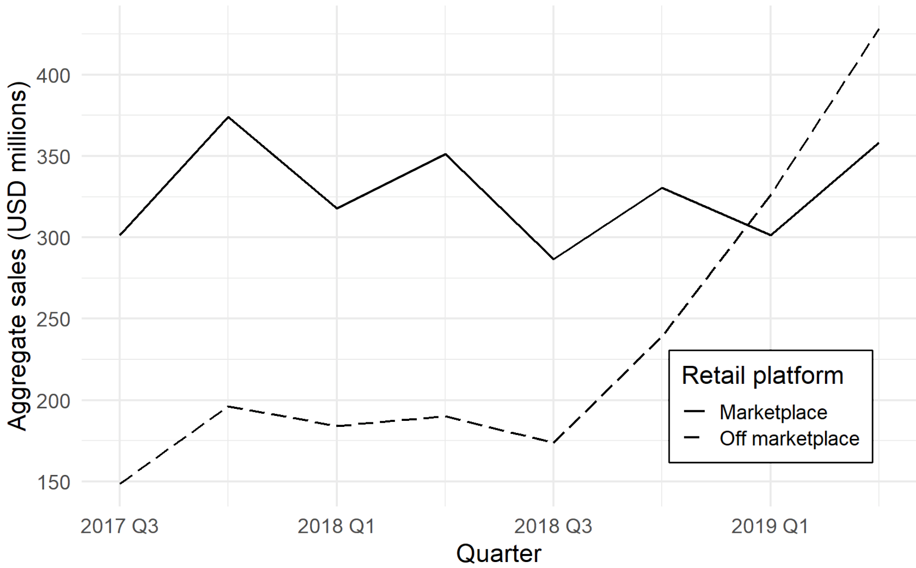
[14] Loans to mPOS merchants were offered starting in the second half of 2018.

Figure 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 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.

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 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 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.

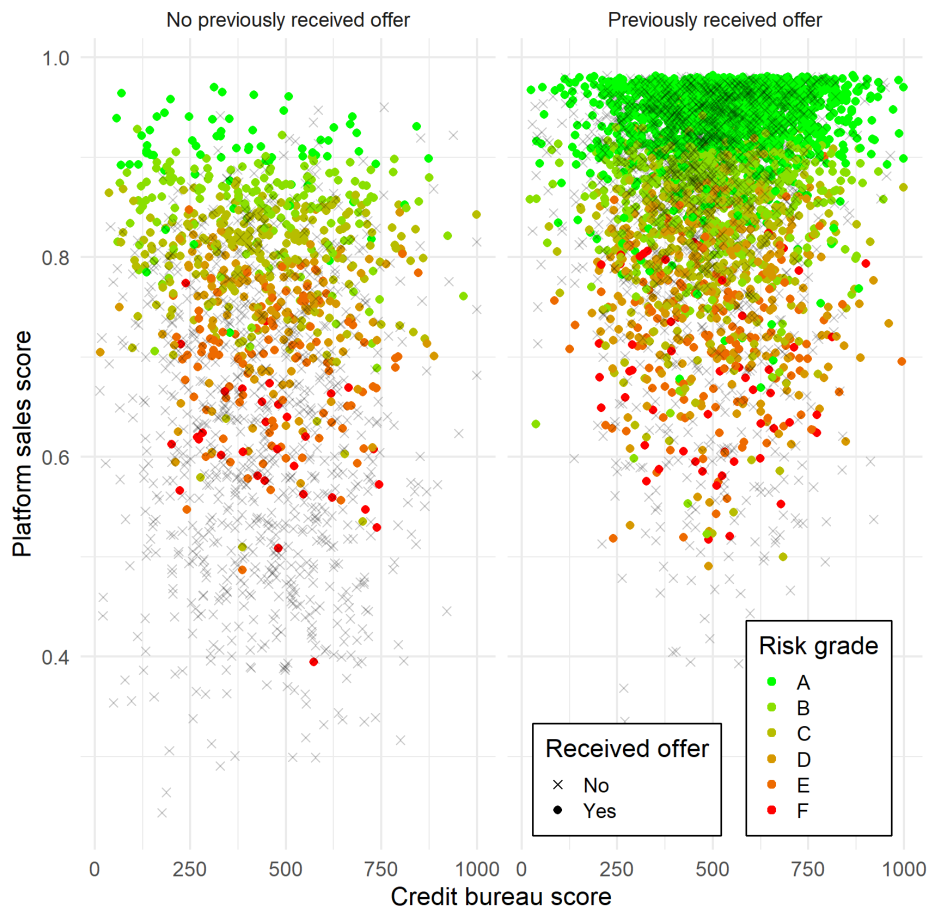
2.4 The impact of a loan offer

Observation 3 *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

[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

Figure 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.

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 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 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 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.

[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.

[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.

3 Theoretical framework

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, Peterson and Silver (2001)[19], the newsvendor setup is appropriate to describe the problem of a retailer

[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.

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 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 5: Inventory model timing assumptions

$t=0$ Decision	$t=0$ Resolution	$t=1$ State update	$t=1$ Decision
Purchase inventory I_{it}	Demand realization d_{it}	Savings yield $r(k_{it}-(A_i+cI_{it}))^+$	Repeat
Pay fixed costs A_i	Revenue $p\min\{d_{it}, I_{it}\}$	Loan costs $r_B(k_{it}-(A_i+cI_{it}))^-$	
Save $k_{it}-(A_i+cI_{it})$		Liquidate inventory $c(I_{it}-d_{it})^+$	

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 compute 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]:

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

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

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

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, Harris and Marschak (1951):

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

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 1. By applying an envelope theorem, the first order condition for any interior solution can be formulated for any value of r_B as:

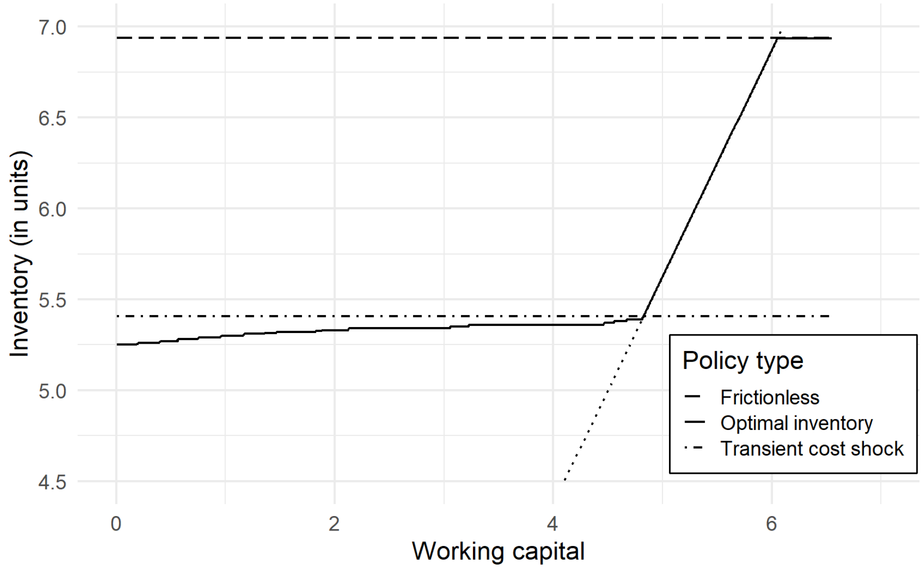
$$p(1 - F_i(I^*))[1 + V'(k'(k, I^*, I^*))] = c[1 + V'(k)] - Rc\int_0^{I^*}[1 + V'(k'(k, I^*, x))]f(x)dx \tag{2}$$

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 6: if working capital is high enough, the unconstrained solution of equation 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.

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

[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.

Figure 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 1, and a 'transient cost shock' policy where the right hand side of equation 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.

needs, the resulting first-order condition matches that of equation 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 6, and reduces the impact of borrowing to a single-period shift in marginal costs.

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.

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

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 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 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.

[23]Some relevant examples of structural estimation of inventory models include Olivares, Terwiesch and Cassorla (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.

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, the binary variable b_{it} that indicates whether a retailer borrows in a given quarter and their revenue y_{it} can be expressed as:

$$b_{it} = \mathbf{1}\left\{k_{it} < A_{it} + c_{it}F_i^{-1}\left(\frac{p_{it} - c_{it}(1 + R(r_{B,it} - r)}{p_{it} - Rc_{it}}\right)\right\} \tag{3}$$

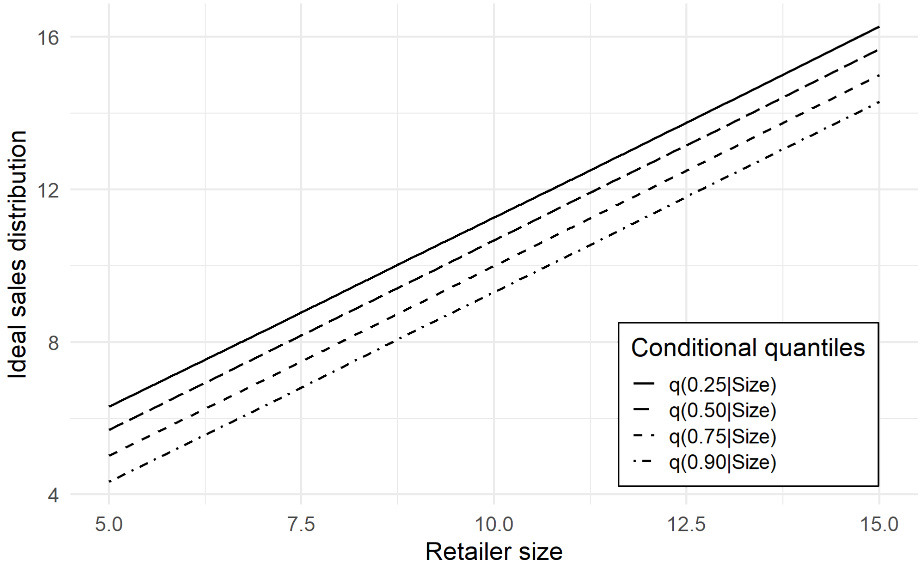
$$y_{it} = \log(p_{it}) + \min\left\{\log(d_{it}), \log F_i^{-1}\left(\frac{p_{it} - c_{it}(1 + \lambda_{it})}{p_{it} - Rc_{it}}\right)\right\} \tag{4}$$

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 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 1 and equals $R(r_{B,it} - r)$ instead for an interior solution with positive borrowing.

Figures 7 and 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 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 credit while accounting for the latent distribution of working assets, demand, and cost shocks that might remain unobserved.

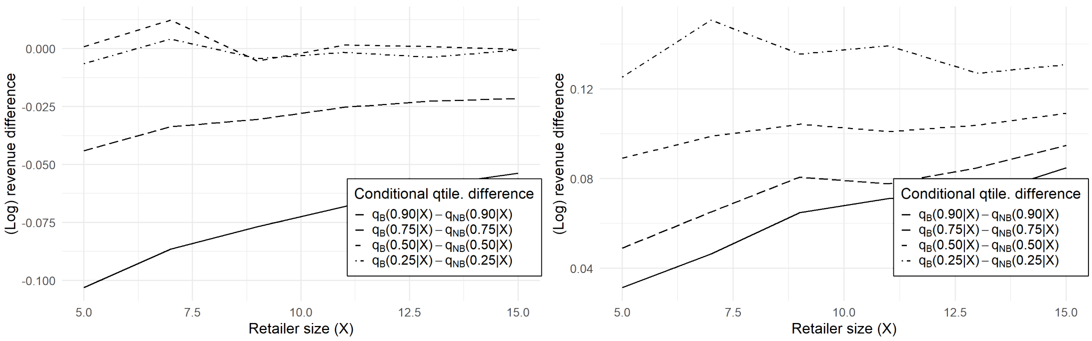
[24]Note that other sources of unobserved heterogeneity might exist, as shown in equations 3 and 4

Figure 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 $d_{it}|X_i \sim N(X_i, 1.5^2)$.

Figure 8: Difference in borrower and non-borrower revenue quantiles, inventory model



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

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 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 3, although F_i is only conditioned on observable X_i.

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 also other primitives of the inventory model, as highlighted in equations 3 and 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 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.

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:

$$y_{it}(x^Y_{it}, u_Y) = q(u_Y|x^Y_{it}) = p\left(x^Y_{it}\right)' \beta_t(u_Y) \tag{5}$$

$$b^0_{it}(x^0_{it}, u_0) = \mathbf{1}\left\{u_0 < P_{0,t}(x^0_{it})\right\} \tag{6}$$

$$b^1_{it}(x^1_{it}, u_1) = \mathbf{1}\left\{u_1 < P_{1,t}(x^1_{it})\right\} \tag{7}$$

The specification for revenue draws from the quantile regression framework, with a basis of third-degree polynomials for covariates x_{it}^{Y} 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 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 4, which might not be binding at lower realizations of demand. Similar applications of quantile regressions include the work of Arellano, Blundell and Bonhomme (2017) to estimate household income and savings processes with panel data.

Equations 6 and 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 2. 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):

$$f(y, b^0, b^1) = f(y) \cdot f(b^0) \cdot f(b^1) \cdot c(F(y), F(b^0), F(b^1)) \tag{8}$$

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:

$$f(y, b^0, b^1) = f(y) \cdot f(b^0|y) \cdot f(b^1|b^0, y) \tag{9}$$

The simplifying assumption of a vine copula model consists of expressing the conditional densities in equation 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]:

$$f(x|\boldsymbol{v}) = c_{xv_j|\boldsymbol{v}_{-j}}(F(x|\boldsymbol{v}_{-j}), F(v_j|\boldsymbol{v}_{-j}))f(x|\boldsymbol{v}_{-j}) \tag{10}$$

With this assumption, every conditional density in equation 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 9 and 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.

Figure 9: Menu 0 vine copula

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

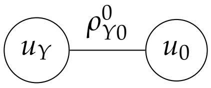
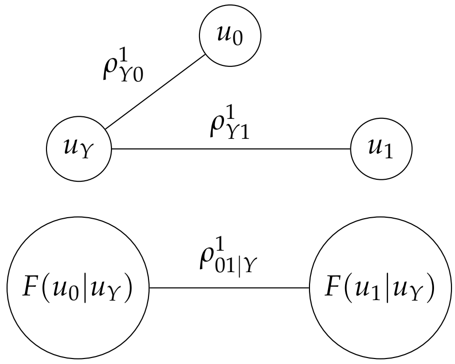


Figure 10: Menu 1 vine copula

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



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

[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.

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 also been identified as a source of adverse selection in consumer lending by Hertzberg, Liberman and Paravisini (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 $\bar{l}_{it}$:

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

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.

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 8. This accommodates latent correlations between mixed-type data, such as discrete borrowing choices and continuous retailer revenue,

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

[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.

and motivates a simple algorithm to estimate the parameters of the empirical model, starting with the marginal distributions of the 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 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:

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

The parameter governing this relationship, ρ_{Y1}^1, 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].

[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, Blundell and Bonhomme (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 10 corresponds to a *canonical vine* (or C-vine) copula with revenue quantile ranks u_Y at the root

[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 $C(u, v; \rho) = -\rho^{-1}\log\left(1 + \frac{(e^{-\rho u}-1)(e^{-\rho v}-1)}{e^{-\rho}-1}\right)$

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:

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

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 2. 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 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.

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 4. The most 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

[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.

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

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 2), 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 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 retailer category and incorporation

[36] For the average low-risk retailer from table 2, 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 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 9 and 10. 95% confidence intervals estimated by subsampling, with 400 subsamples of size 4000.

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.

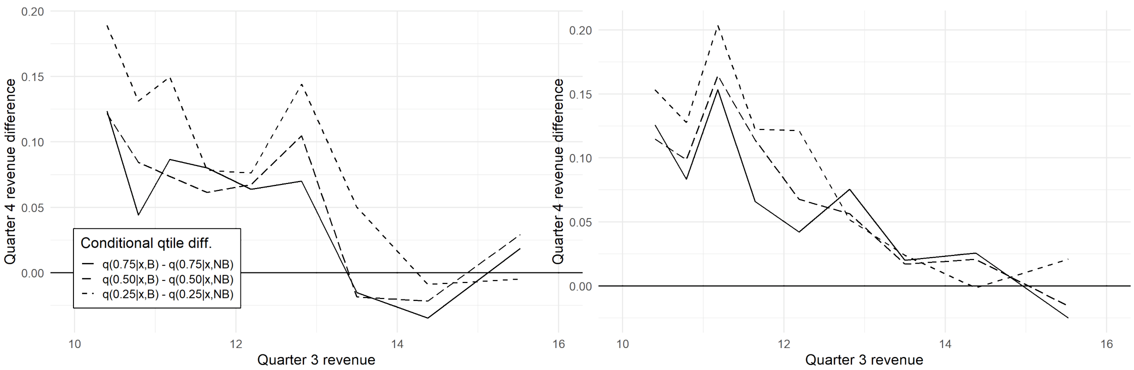
5 Counterfactual Analysis

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 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,

[38] Contrast figure 11 with the corresponding figure 8 generated from the inventory model.

Figure 11: Difference between borrower and non-borrower revenue distributions



(a) Low credit score (b) High credit score

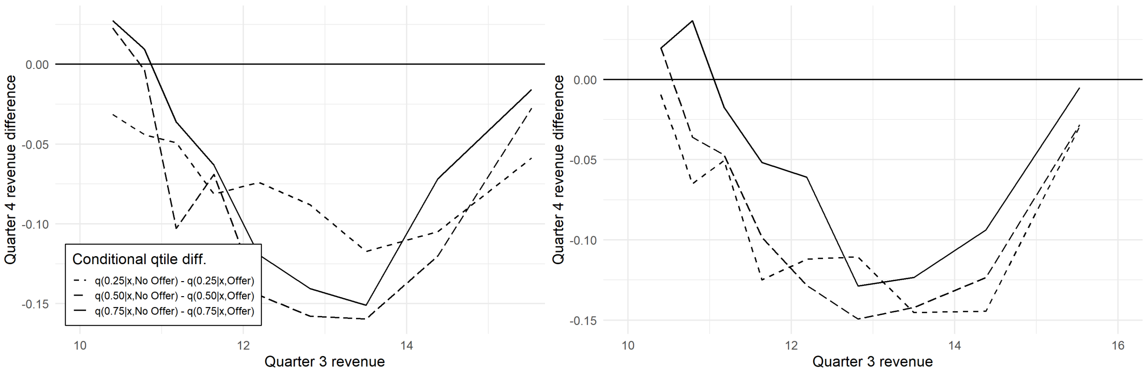
Notes: Difference between the distribution of borrower and non-borrower quarter 4 (2018 Q2) revenue, assessed at four quantiles and conditional on blocks of retailer size, defined as revenue in the previous quarter measured in log ARS, and divided between low and high-credit score borrowers using the same criterion as in table 2. 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).

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 12 and 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 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.

[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.

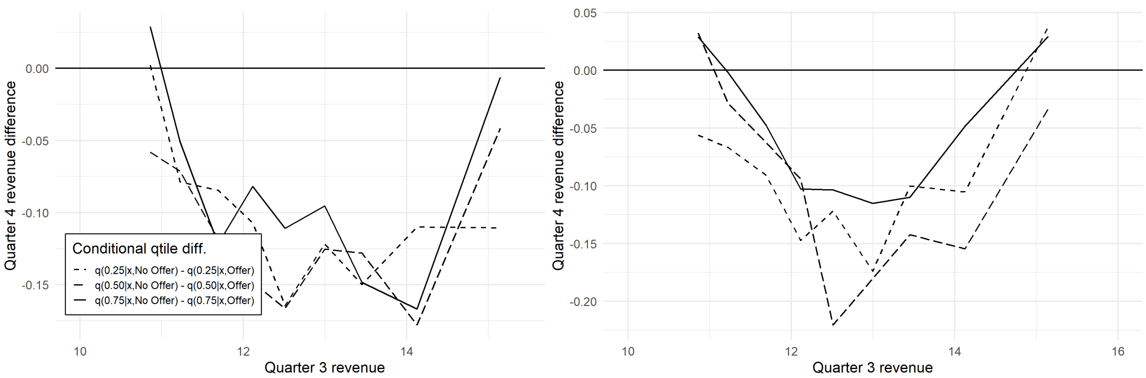
Figure 12: Simulated distributions, with and without platform borrowing option



(a) Low credit score (b) High credit score

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.

Figure 13: Simulated distributions, with and without platform borrowing option, refinancers



(a) Low credit score (b) High credit score

Notes: Same as figure 12, but limited to retailers with positive liabilities owed to the platform at the beginning of the fourth quarter.

6 Conclusion

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

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

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 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.

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Appendix

Appendix A - Estimation of loan offer propensity scores

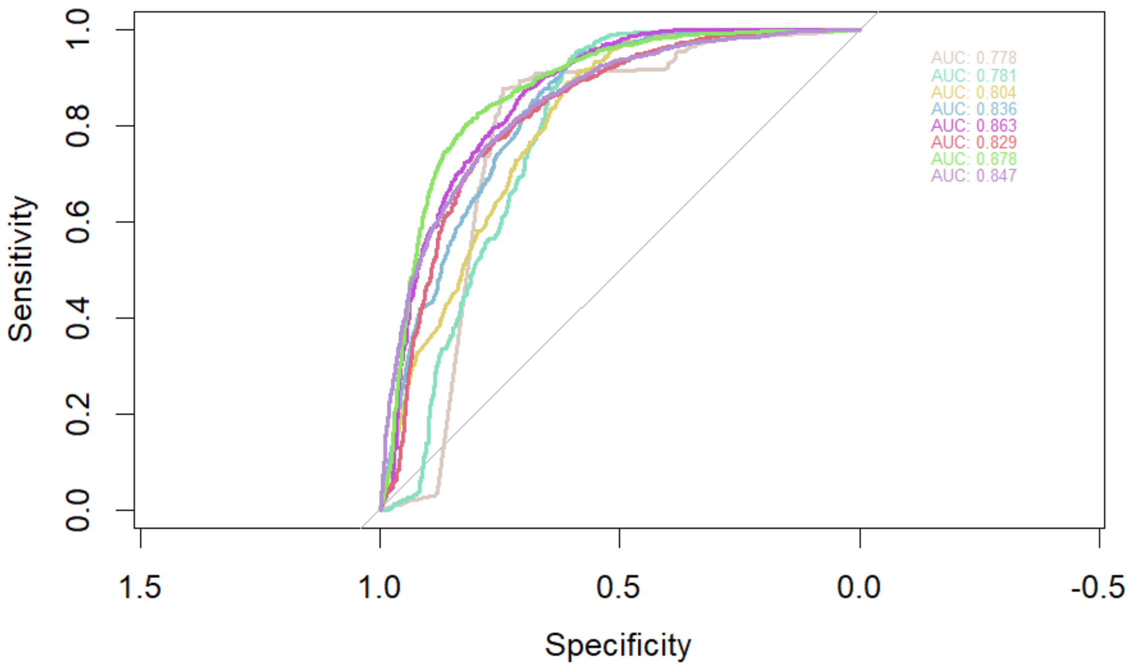
The dataset used for this analysis crucially includes many internal variables that the platform employs for the purpose of screening lenders and determining loan offers. However, figure 4 highlights that the platform's decision to lend, while indicative of some score-based thresholds, presents only small 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 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 14. 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 14: 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 $\mathbf{1}\{NB\} = 1 - \mathbf{1}\{B\}$:

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

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

$$\begin{aligned} E_X\left[V'(k'(k,I,x)\frac{\partial k'(k,I,x)}{\partial I}\right] &= p(1+r)(1-F_i(I))V'(k'(k,I,I)) + c\int_0^I V'(k'(k,I,x))f_i(x)dx - \\ &cE_X\left[V'(k'(k,I,x)\frac{\partial k'(k,I,x)}{\partial k}\right] \end{aligned} \tag{11}$$

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

$$V'(k) = \frac{r_B - r}{1+r}\mathbf{1}\{B\} + RE_X\left[V'(k'(k,I,x))\frac{\partial k'(k,I,x)}{\partial k}\right] \tag{12}$$

By replacing the expected marginal continuation value of inventory in the first order condition with the expression in equation 11, subsequently substituting the marginal value of capital from equation 12 yields the reformulated first-order condition 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.