"Do you accept Pix?": The effects of fast payments on firm external finance

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Abstract

Fast payment systems (FPS) provide merchants with immediate access to funds from sales and generate granular data on transactions. This contrasts with credit and debit cards, where funds are available with a lag, or cash, which does not generate transaction data. These liquidity and informational changes can affect firms' demand for, and ability to obtain, external finance since, all else constant, firms whose clients pay more with FPS are more liquid and easier for creditors to monitor. We build a model that endogenises the choice of payment methods by firms and customers as well as their implications for firm financing. Using granular firm-level data on Brazil's FPS Pix, we then explore the financial and real effects of fast payments on firms. Using the share of Pix payments in non-cash income as a firm-time-level indicator, we find that when firms receive more Pix payments, they obtain higher credit limits, but take up less in loans and have better repayment behaviour. The results are supported by estimations with robberies as an instrumental variable for the willingness to use cash. The findings appear consistent with, among other channels, an improved liquidity profile of firms that receive more sales proceeds through Pix.

Keywords: Payments, firm liquidity, credit.

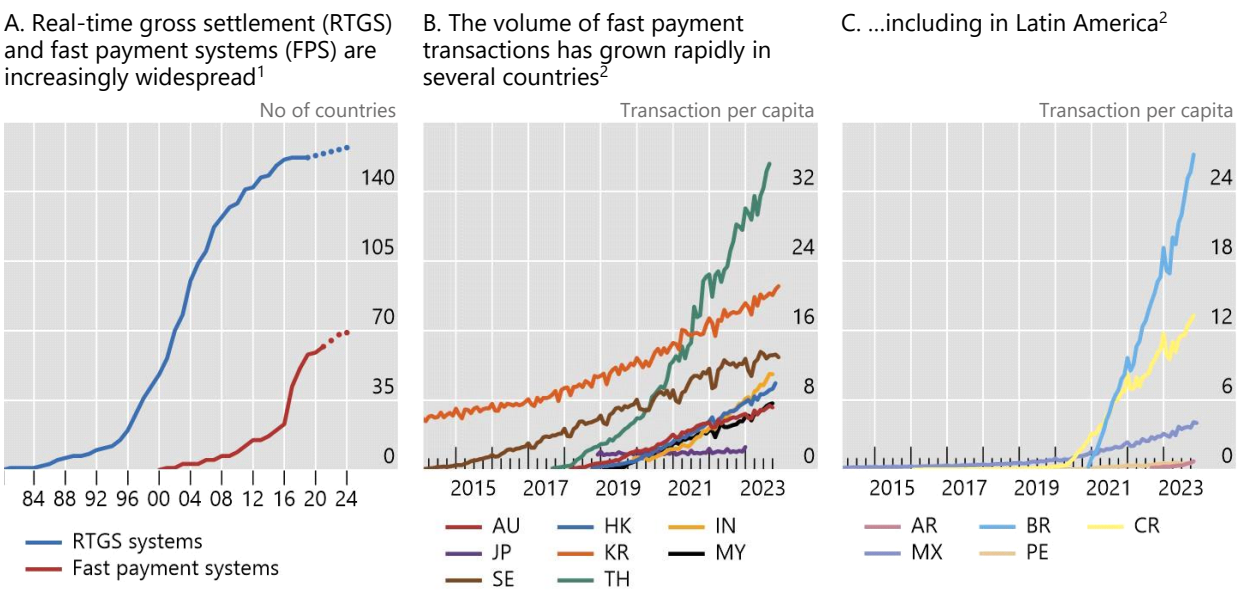
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1. Introduction

Accelerating changes in the payment landscape are affecting liquidity and informational availability, and thus may also affect firms' financial choices. These developments are exemplified in particular by fast payments systems (FPS), which allow households and businesses to make transfers that are immediately available to the recipient on a 24/7 basis. In addition, payments through FPS usually make the identity of the payer known to the receiver and its bank, unlike anonymous cash payments or many payment cards. FPS have seen quick adoption in a number of jurisdictions (CPMI (2021); Frost et al (2024)). Just as with the roll-out of real-time gross settlement (RTGS) systems two decades ago, a growing number of countries now have FPS (Graph 1, panel A). In countries like Brazil, Costa Rica, India and Thailand, fast payments have seen rapid adoption by most adults, with multiple transactions per month (Graph 1, panels B and C).

A growing number of countries have fast payment systems — Graph 1



[1] The dotted part of the line corresponds to projected implementation. [2] Monthly data.

Source: CPMI (2021); Individual central banks; IMF; World Bank; National Payments Corporations of India; Hong Kong Interbank Clearing Limited.

In this paper, we use the case of Pix in Brazil – a key example of an FPS in a large and diverse emerging market economy (EME), launched in November 2020 – to explore how these new payment modalities impact firm outcomes. We use confidential data from the Central Bank of Brazil (BCB) to explore firm-level variation in the value and share of incoming non-cash payments by modality, including Pix. These data are connected to other confidential datasets, namely comprehensive credit and employment registries, to further complement the firm-level view. Informed by a theoretical model that links external financing and payment method decisions, we regress firm-level external financing outcomes against the contribution of Pix payments to total measured income. In these regressions, we control for changes in their overall income, to focus on the effect of Pix on firms. Given the widespread adoption of Pix as a person-to-person (P2P) and person-to-business (P2B) payment system in Brazil, we focus on retail firms.

As motivation for this somewhat unintuitive quest – beyond the sales amount itself, why should the *payment method* lead to different firm outcomes? – we build a model inspired by Holmström and Tirole (1997) in a setting where firms endogenously borrow from banks to finance a retail project, in which customers can pay using one of various methods. Each method has implications for the liquidity of firms, households and for the information available to firms and banks. From this model, we learn that there are several ways in which such payment innovations might influence firm outcomes. For one, vendors' liquidity might improve if Pix payments substitute for credit and debit cards. For credit and debit cards, funds are only available after several days (or require costly discounting) and merchants often pay costly merchant discount rates. Another channel of influence may come from the more detailed information available to prospective lenders, who can more easily monitor borrower firms' activity in real time as individual payments come in. This contrasts sharply with cash, and to some extent with payment cards, for which data are often aggregated and only available with a lag.[2] Beyond this, firms themselves may take advantage of the information on individual customers (since Pix payments are identified) to better learn customer wishes, whenever there is sufficient scale for this. More broadly, the availability of Pix increases sales convenience such as making some (eg online) products more accessible to consumers without a payment card. All of this might make it worthwhile for the firm to invest more in sales efforts.

In practice, when looking at the retail sector, Pix might affect firms through a few of these channels at the same time. We first show the wide-ranging effects of higher shares of Pix inflows on firms and find striking results, even after controlling for observed and unobserved firm-level characteristics. Firms with more Pix payments relative to overall (non-cash) income benefit from higher credit limits from banks. The evidence on credit use is less clear-cut, but nonetheless suggestive that these firms take up less in loans. What is clear though is that firms improve repayment behaviour with greater share of Pix income. This would be consistent with an improved liquidity profile that gives them greater access to loans, even while their use of loans is lower. Another potential channel is the improved sales from the higher convenience to customers from accepting Pix.

After its launch, Pix was adopted rapidly by users across Brazil. Adoption was influenced by local conditions, such as availability of mobile internet connectivity and the footprint of different banks in different municipalities. Still, we consider for robustness a scenario where there might be some endogeneity. Since firms also anticipate some of the benefits from receiving a higher share of their revenue as Pix, they might undertake actions that influence consumers' choice of payment method. We have observed in the field that some retail stores, for example, offer discounted prices for Pix payments given the lower fees that they pay on Pix transactions. While our main estimation strategy already accounts for the confoundedness of payment methods and firm external financing, we also address this endogeneity in our main explanatory variable of interest by instrumenting it with the variation of robberies in the cross-section of municipalities when Pix was first implemented nationwide. Different levels of robberies shift consumers' ability and willingness to use Pix as a payment modality, but not firms' incentives or ability to accept or promote Pix as a payment modality. This analysis is restricted to São Paulo state due to data availability. We also look specifically at the retail sector across Brazil, which may be most clearly impacted by Pix payments given its popularity for P2P and P2B payments. The results from these exercises are consistent with our baseline and provide support for a causal effect of Pix payments on firm outcomes.

Our paper contributes to the literature on the real effects of payment innovations. Like Jack and Suri (2014) and Breza et al (2020), we find real benefits to users from digital payments with micro data. Yet while these studies focus on households, we look at benefits for firms. To our knowledge, ours is the first study to look at the benefits to Brazilian firms of accepting Pix payments. This has broad relevance for other countries around the world that have launched or are considering FPS. Our paper is most closely

[2] Due to the contemporaneous implementation of open banking in Brazil, even lenders with which a firm does not have a direct relationship might benefit from the available information set from Pix payment inflows.

related to Sarkisyan (2024), who studies the effect of Pix on bank competition for deposits and finds that it significantly increases the demand for deposits at smaller banks, leading to lower deposit rate gaps compared to larger banks.

More broadly, our work is related to the long literature going back to Meyer and Kuh (1957) focusing on firm financial constraints and its real effects.[3] Fazzari et al (1988) are an influential early contribution to this literature, linking firm investment to cash flow measures of financial constraint (and noting that many smaller firms are in the more constrained group). Kaplan and Zingales (1997) question this identification method by showing that the investment of firms that appear less financially constrained is actually more sensitive. Whited and Wu (2006) use a different method to identify financially constrained firms and show that a financial constraints index is a driver of cross-sectional returns. However, most of this literature focuses on firms that are large enough to be publicly traded, even if they are relatively small. In our case, we study a markedly more comprehensive set of firms, most of whom are well below the size of publicly traded firms and thus rely primarily on bank finance for external funds.

The next section introduces Pix and the broader context of firm financing in Brazil. Section 3 presents a simple theoretical model of externally financed firm investment, in an arrangement subject to moral hazard. We then describe the data and empirical analysis in section 4, including results from an instrumental variable approach. The final section lays out our conclusions.

2. Institutional setting

Pix is a fast payment system developed and operated by the BCB, launched in November 2020. Pix combines an information technology (IT) infrastructure and a rulebook with specific rules and standards for banks to ensure consistent operational and service levels. The infrastructure includes a settlement system – an RTGS called the Instantaneous Payment System (SPI) – and a proxy database (DICT), which matches aliases (eg mobile phone numbers and e-mail addresses) to account numbers.[4] The combination of the infrastructure and the rulebook enables a uniform user experience for households and businesses. Both bank and non-bank payment service providers (PSPs) are eligible to offer transactional accounts to end consumers. Rules also enforce a standardised user experience in mobile apps. To initiate a payment, users use the online banking app of their own bank or non-bank PSP. They only need to enter the payee's bank account information or an alias (such as a phone number or e-mail address), or to scan a quick response (QR) code. They enter the amount to be transferred and both the payer and payee receive a confirmation that the funds have been transferred. All of this means that using Pix is equally easy to users regardless of their preferred PSP.

Brazilians have adopted Pix very rapidly (Duarte et al (2022)). By December 2022, more than 71 million individuals had made their first digital payment with Pix.[5] Over that same period, Pix already represented 40% of the volume of digital payment transactions in Brazil, according to BCB data. At the end of 2022, 133 million citizens (77% of the adult population) and 11.8 million companies held a total of 551 million aliases.[6]

[3] The macroeconomic implications of financial constraints are studied by, among others, Bernanke and Gertler (1989), Bernanke et al (1996) and Kiyotaki and Moore (1997).

[4] See Annex for more details.

[5] This number includes the total number of individuals that had not previously paid with wire transfer, the primary digital method before the advent of Pix, between November 2019 and November 2020.

[6] Authors' calculations based on the BCB 2023 Pix management report and BCB Pix statistics.

A combination of design decisions explains the quick adoption by such a large and widespread population as in Brazil (Duarte et al (2022)). First is the pricing: PSPs are not allowed to charge any transaction fees to individuals acting as either payers or payees, regardless of the amount.[7] Firms, on the other hand, are subject to a competitive fee schedule, with merchant discount rates of 0.22% on average, compared with 2.1% for credit cards and 1.1% for debit cards (Graph 2, panel B). The pricing structure implies low switching costs for individuals and households and allows for cash-like purchases with low average ticket sizes, which intensified within the first months after launch. Another contributor to adoption comes from strong network effects (Farrell and Klemperer (2007)): the BCB mandated at the outset all banks and non-bank PSPs with over 500,000 active transaction accounts to participate. In effect, all large banks had to offer Pix services to their clients, which stimulated other PSPs to do the same. This created conditions to onboard millions of customers to Pix from launch.

Other design choices raised awareness about Pix and steered it towards user convenience, further catalysing adoption (Brandt and Lobo (2021)). The BCB set up a widespread communication strategy that included strict branding policies and rules, as well as standardised user experiences and minimum requirements for user interfaces. This made Pix transactions have a similar "look and feel" for all users, regardless of the bank or non-bank PSP they have an account with. Since both price and experience were standardised, the end-to-end experience would be very similar across PSPs, pushing them to provide clear benefits for their customers. Conjunctural factors also played a role, since the launch period coincided with the Covid-19 pandemic, when Brazil's population was subject to varying levels of mandatory or voluntary isolation and a rise in remote transactions (eg e-commerce).[8]

Because of all these factors, Pix became a popular payment method for retail transactions (Graph 2, panel C). This sets the backdrop upon which financial intermediaries competed to provide new products to their customers, to evolve their business models and to take advantages of the high uptake of Pix by the Brazilian society. With the factors above, it is reasonable to assume that the economy-wide adoption of Pix in a short period of time reflects a combination of macro-level policy (and design) decisions with local (municipality) conditions, as opposed to the specific circumstances of any given firm or industry. This is shown objectively through a comparison of adoption rate regressions on time trends and a range of fixed effects. In all these regressions, the dependent variable is a municipality's share of firms that have enabled Pix transactions in their accounts and the main covariate is the number of quarters since Pix was launched; the baseline regression has no fixed effects. The second specification contains municipality fixed effects; a Wald test shows that municipality-level constants are statistically significant, consistent with local factors driving average adoption. The third specification contains sectorial fixed effects, which are not statistically different from the unconstrained baseline regression. The fourth specification combines municipality and sector fixed effects. The fifth approximates firm-specific results by combining municipality-sector-size buckets. These results help us see that, while adoption rates are associated with time and municipality-specific dynamics, variation closer to firms did not meaningfully explain adoption of Pix. This reinforces the claim that this is a quasi-exogenous change in how clients tend to pay for goods.

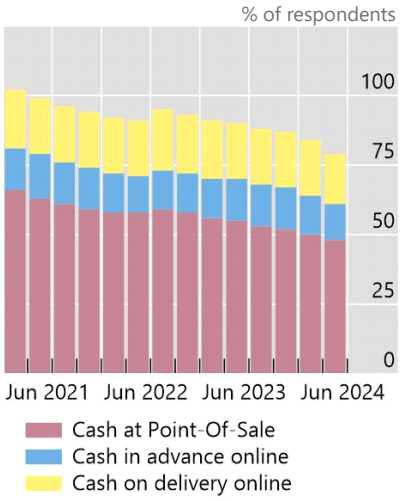
[7] Individuals who use their accounts to transact in a merchant-like manner can be charged if they receive more than 30 transactions per month. There are never fees to initiate a Pix payment.

[8] The Covid-19 pandemic also helped the adoption of another FPS, Costa Rica's SINPE Móvil (Araujo et al (2024)).

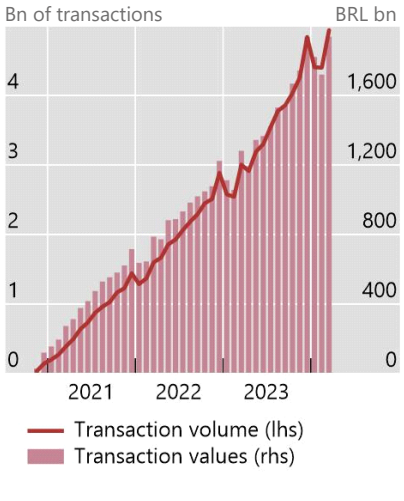
Brazilians adopted Pix en masse

Graph 2

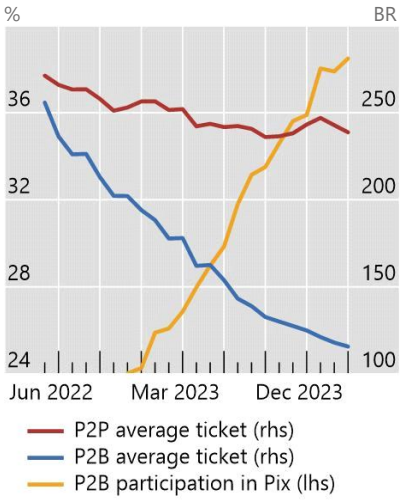
A. The share of cash transactions has declined[1]



B. Pix transactions have soared



C. Average ticket and share of P2B indicates retail usage of Pix



[1] Data obtained from Statista's Consumer Insights surveys, which asked respondents about their use of cash at Point-of-Sale (POS) and for online payments. Percentages do not necessarily sum to 100% as respondents could select multiple payment methods. P2P = person-to-person, P2B = person-to-business.

Source: Central Bank of Brazil; Statista.

From the perspective of the merchant receiving a payment, Pix is different from previously existing payment methods in a number of important ways. The most prominent one is its liquidity: in contrast to credit (and less so debit) cards and payment stubs, but similar to cash, Pix payments settle instantly. In terms of information provided to actual or potential lenders, Pix payments offer real-time, hard data on sales – analogous to the information provided by cards and payment stubs but in contrast to the lower information level from cash sales, which can be underreported (eg for tax purposes). And in terms of information about clients, firms receiving Pix retain as a by-product the exact identification of each client just as with payment stubs, which is not the case with cards (absent any loyalty programme or white labelled cards) and of course, in full contrast with the anonymity of cash.

3. Theoretical framework

Having established the significance of Pix and how different it is from other existing payment methods, this section lays out how we expect Pix could affect firms, serving as groundwork to motivate the empirical strategy that estimate those effects. In particular, it lays bare *why* should the *payment method*, not the paid amounts, matter for firm outcomes. One challenge demonstrating this is that firm external financing depends, crucially, on how banks estimate the impact of Pix to be on firms. In addition, given the macroeconomic scale of Pix adoption, another challenge that we need to overcome when postulating the effect of Pix on firm financing is to show that an overall change in lending supply would be expected.

To address these obstacles, we model the effects of Pix on firms with a simple theoretical model of firm production and financial intermediation inspired on Holmström and Tirole (1997). We adjust the model to explore the effect of payment methods on financial and real outcomes of financially constrained firms, rather than focus on the distribution of firms or on the distribution of capital between types of

agents. Our version of the model is a static equilibrium model to allow us to focus on the novel ingredients we introduce: bank deposits, a retail sector and payment costs.[9] The model also underscores unobserved factors that can confound estimation of the effect of Pix on firms from the customer and from the firm side; helping to establish an empirical strategy to identify the effects of Pix on firms. We then lay out theoretical predictions of our model and a comparative static exercise when a costless, immediate payment technology such as Pix is introduced. These theoretical predictions are then compared with our empirical findings in Section 4.

3.1 Model

There are two periods, decisions (T0) and payoffs (T1), and three types of agents in this economy: (1) firms, further grouped in two sectors, (2) a competitive banking sector and (3) households, who earn profits from firms as shareholders and consume the proceeds in retail transactions. One sector of firms competitively sells capital goods to other firms and is not further modelled. In the other sector, rationalised as retail, a representative firm has one economically viable project that requires a level of investment *I*. This investment is also socially valuable in expectation, such that retail firms will always undertake the investment regardless of any decision of any other agent. Recall that the use of Pix is quite standardised, which together with the introduction of open banking, lends credibility to the hypothesis of a competitive banking sector. Households can also be seen as shareholders of the banks and of firms in the capital goods sectors, but as these sectors are competitive and thus zero-profit, the models' predictions are the same.

In this model, the investment amount equals the firm's available assets $I = A$, which allows us to concentrate on the economically interesting case in which any external financing occurs only if it is a rational choice of the firm. The firm's asset is the combination of its cash holdings A_0 that are deposited at banks to earn a rate α in T1 and a productive asset A_p, ie $A = A_0 + A_p$. That productive asset is either used in a project or depreciates fully if not used, in which case it becomes a write-off expense in T1. When investing in the project, the productive asset is more valuable to the firm than spending cash, which has a valuable outside option of earning the deposit rate. For this reason, when deciding the investment mix in T0, the firm first deploys A_p before tapping their deposits A_0 if they are needed to self-finance investment.

The project can either fail or succeed, respectively returning 0 or a positive amount *R* in T1. Firms have a baseline probability of success $0 < p_l < 1$. The retailer can try to increase the chance of success by exerting effort. If the firm does not exert any effort, firm managers accrue a wasteful, private benefit B that does not flow to firm shareholders (who are, ultimately, households). At the expense of this internal benefit, efforts may increase the chance of success to p_h by an amount $\Delta p = p_h - p_l$. But while any effort foregoes managers' private benefit B with certainty, the probability of success only effectively increases to p_h if the firm's effort actually appeals to customers. For example, accepting user-friendly and affordable payment methods; making stronger sales efforts; offering discounts; advertising in a way that is suitable to a particular clientele, stocking products that appeal more to the tastes of the firms' clientele, etc are all firm efforts that may all help to increase the probability of success.

In other words, the probability of success only goes to p_h if the retailer exerts an effort that successfully matches the customer taste; merely exerting the effort (ie, foregoing the private benefit B from slack) does not guarantee success. Concretely, $\eta \in \{-1, 0, 1\}$ represents the firm's effort set. Note that under this

[9] Santamero and Seater (2000) also expand Holmström and Tirole (1997) to a general equilibrium setting, but their goal is to study the optimal size of the financial sector when it is endogenously determined. Note also that while Holmström and Tirole (1997) use a notation similar to the one above to refer to individual firms, which are then aggregated in a distribution for firms, in this paper the notation refers to representative agents for simplicity. This simpler notation retains the familiarity many readers have with the Holmström and Tirole (1997) model while affording a way to focus on the equilibrium characteristics and in particular on the comparative statics when a new payment choice is introduced.

parametrisation, -1 and 1 are not the *levels*, *costs* or *quality judgments* of the firm's effort but a non-zero attempt to match customer tastes $\theta \in \{-1, 1\}$. If $\eta = \theta$, equation 1 reduces to $p_h R$, or to $p_l R$ otherwise. To summarise, the case of $\eta = 0$ means the firm exerted no effort, and $\eta \neq 0$ means the firm undertook the effort to attempt to match the customer taste, but the project only has a high chance of success if $\eta = \theta$.

This effort is subsumed within a summary statistic that can take opposite values for simplicity and analytical tractability.[10] At T0, only the customer knows their own tastes, and the firm only learns about them in T1. The project expected gross earnings $\hat{R}$ are then the revenue earned if successful, R, weighted by its success probability. This probability is at least p_l but can increase by Δp to p_h if the firm matches the customer taste, since the term $(\eta\theta + 1)\eta^2/2$ simplifies to 1 if $\eta = \theta$ or to 0 otherwise. This is laid out in the formula for the expected return, $\hat{R}$:

$$\hat{R} = \left(p_l + \frac{\Delta p(\eta\theta + 1)\eta^2}{2}\right) R \geq 0. \qquad 1$$

The firm may or may not require a loan, but taking out such external financing has implications for the firm's operations. If the firm fully self-finances the project, without any loan, it will productively use all of A_p and also A_0, foregoing the deposit interest αA_0 earned at T1. Conversely, in exchange for a loan L, $0 < L \leq I$, the firm pledges to use part of its gross return to remunerate the bank, which it can do if the project is successful; the promise is unfilled otherwise. In case of success, out of the gross project income R, the firm retains R_f and pays R_b to the bank: $R = R_f + R_b$, all positive. The bank's payoff R_b in currency is determined by the loan amount and an interest rate β, with $\beta = R_b/L$.

For small loan amounts, $0 < L < A_0 < I$, the firm uses all of its productive asset A_p and also a part of its initial deposit to complete the amount I. In this case, the firm must spend an amount of deposit equal to $I - L - A_p$ to help fund the investment, and this amount then does not earn interest α in T1. The remaining amount of deposits after investing coincides with L. For larger loan sizes, in particular if $0 < A_0 < L < I$, the firm is able to retain the totality of its original cash holdings. Note that in any case, the firm's liabilities increase by L to $A_0 + A_p + L$, with the first two terms equating the original equity, previously invested only in cash and productive assets, and the firm's assets now sum up to $I + \min(A_o, L) + \max(0, L - A_0)$.

Define $\hat{\theta}$ as the firm's belief about consumer tastes; $A_0^* = \min(A_0, L)$, $0 \leq A_0^* \leq A_o$, as the remaining deposits after investing; and $A_p^* = \max(0, A_p - I + L)$ as the residual amount of unutilised productive assets after the firm invested, which then fully depreciates and becomes a firm expenditure in T1. Define also $R_b^* = R_b$ if $L > 0$ and 0 otherwise and $R_f^* = R - R_b^*$. Then, a generic formulation of the firm's expected (at T0) payoff at T1 considering all possible effort and success scenarios is the following:

$$u(F) = \left(p_l + \frac{\Delta p(\eta\hat{\theta} + 1)\eta^2}{2}\right) R_f^* + \alpha A_0^* - A_p^* + (1 - \eta^2)B. \qquad 2$$

Equation 2 nests all possible scenarios. If the firm does not make an effort, the firm's payoff is $p_l R + \alpha A_0 + B$. In this case, in T1 the firm's chance of success is low, but it still receives compensation for its initial bank deposits and its managers earn the private benefit. Alternatively, if the firm decides to make an effort, two potential payoffs lay ahead. If the firm's effort does not match consumer preferences, the payoff is $p_l R_f^* + \alpha A_0^* - A_p^*$: the firm retains its own portion of the revenue, itself obtained with low probability, earns the deposit rate on unspent deposits while still writing off the unused portion of the productive asset. Finally, if the effort is successful, the expected payoff is $p_h R_f^* + \alpha A_0^* - A_p^*$. In this scenario,

[10] Thus, the model is close in spirit to matching games literature started by the landmark work of Gale and Shapley (1962), but in this case the focus is on a representative firm matching the exogenous tastes of a representative consumer. In addition, the matching taste is parameterised in a way as to facilitate the analytical demonstration of the point that the firms' utility depends in part on successful matching.

the firm earns revenue with high chance, plus the deposit rate on unspent deposits, from which the firm subtracts the requirement amounts to replace any used portion of the productive asset.

Since the firm's payoff in T1 is actually lower for a failed effort than if the firm had not exerted effort, the firm only exerts effort when the expected payoff in this scenario is greater than or equal to the no-effort alternative, with equality assumed to favour investing. Simplifying $\frac{(\eta\tilde{\theta}+1)\eta^2}{2}$ to q (explained in more detail below), the firm's incentive constraint for investing with effort is:

$$(p_l + q\Delta p)R_f^* + \alpha \min(A_0, L) - A_p^* \geq p_l R + \alpha A_0 + B \therefore$$
$$R \geq \frac{B + A_p^* + \alpha(A_0 - \min(A_o, L)) + (p_l + q\Delta p)R_b^*}{q\Delta p}. \qquad 3.i$$

Equation 3.i shows that the effort gross payoff, if successful, must be sufficient to compensate the lost utility, regardless of whether the firm takes out a loan or not. If equation 3.i holds, the decision to undertake the effort makes sense and the firm decides in in T0 to invest. But the next question, namely whether the firm finances the investment with a loan, depends on how 3.i unfolds if $\eta \neq 0, B = 0, L > 0$. Replacing $A_p = I - A_0$ yields $A_p^* = \max(0, L - A_0)$. Two scenarios arise. If $0 < L < A_0$, 3.i becomes $R \geq (B + \alpha(A_0 - L) + (p_l + q\Delta p)R_b)/(q\Delta p)$. Conversely, for the range $A_0 \leq L \leq I$, equation 3.i turns into $R \geq (B + L - A_0 + (p_l + q\Delta p)R_b)/(q\Delta p)$. Armed with this description of both cases of the firms' borrowing circumstances, we can analyse the incentives for the firm that makes an effort to demand external financing.

We are broadly interested in the case of cash-strapped firms, where the bank deposits are sufficiently low to be smaller than realistically obtainable loan amounts, $A_0 \leq L$. Concentrating in this scenario and simplifying equation 3.i using $\beta = R_b/L$ yields the following quadratic constraint that loan contracts must comply with for the firm to decide to get a loan:

$$L^2 - L(q\Delta pR - B + A_0) + (p_l + q\Delta p)\beta \leq 0, \qquad L \geq 0 \ \therefore$$
$$0 \leq \underline{D}(L) \leq D(L) \leq \overline{D}(L) \leq I, \qquad 3.ii$$

where $D(L)$ represents the firm's demand for loans, bounded from below by

$$\underline{D}(L) = \max\left(0, \frac{1}{2}[\mathrm{A}_0 + \mathrm{q\Delta pR} - \mathrm{B} - [(A_0 + q\Delta pR - B)^2 - 4(p_l + q\Delta p)\beta]^{\frac{1}{2}}]\right)$$

and from above by

$$\overline{D}(L) = \min\left(\mathrm{I}, \frac{1}{2}[\mathrm{A}_0 + \mathrm{q\Delta pR} - \mathrm{B} + [(A_0 + q\Delta pR - B)^2 - 4(p_l + q\Delta p)\beta]^{\frac{1}{2}}]\right).$$

The item $A_0 + q\Delta pR - B$ intuitively is correlated with the expected payoff for the firm under effort and with external financing, due to the ability to retain its deposits earning the deposit yield. Put clearly, the bounds for the demand for loans (or the exact value when there is only one root) is determined by the roots to the Bhaskara equation that solves the inequality. For example, with a reasonable calibration,[11] the firm demands 13% of the project to be funded by loans; but if it failed to finance at least 3% with loans, the firm would not undertake the effort.

Between the bounds of 3.ii, firms respond to demand factors. In particular, factors that increase the firm's demand bound for loans are a firm's cash position, which earns a safe outside option rate; the project's overall gross remuneration R; its chance of success q; and the differential in the probability of earning the success rate, Δp. Since borrowing is costly, an increase in loan interest rates β lowers the demand for loans.

[11] According to a model calibrated as such: $q\Delta p = 50$ percentage points (pp), $p_l = 25$ pp, $B = 1\%$, $\beta = 30\%$, $R/I = 15\%$ and $A_0/I = 10\%$.

The dependency of the loan demand equation on q links the firm investment decision with this ability to divine customer tastes. A growing literature explores this theme of data helping improve matching between disjoint sets of agents (employers with employees, firms with consumers, etc); see Kirpalani and Philippon (2020) and Bergemann et al (2022) and, for a recent overview of the data literature, Veldkamp and Chung (2024). In the current model, the firm's ability to model consumer preferences starts with a random guess if the firm has no information about customers and increases with the amount of client data. Consider the firm's outlook for customer preferences, $\hat{\theta} = \theta(-1)^{\mu}$, where μ is a Bernoulli-distributed variable that takes the value of 1 with probability p and 0 with probability $q = 1 - p$. If $q = \sigma(\pi_q Q)$, for σ representing the sigmoid function, π_q some unimportant non-negative monotonic parametrisation[12] and Q the non-negative amount of data about potential clients, then firms with more client data will be more likely to correctly estimate customer demand and therefore will be self-motivated to exert effort regardless of their financing needs. This is related, for example, to recent findings by Eeckhout and Veldkamp (2024), who note that firms with more client data have higher markups even when controlling for pricing power. Note that the expected value of $\frac{1}{2}(\eta\hat{\theta} + 1)\eta^2$ is q, while its actual value is either 0 or 1. Because the focus is on the information setting, all agents are risk neutral for simplicity.

Banks offer deposits to firms and households, A_0 and H_o, and on the other side of their balance sheet, provide loans to the firm to help fund its investment projects, L, and keep the remainder in riskless government bonds, T.[13] Since banks are competitive, they offer deposit holders in T0 the same interest α that they earn in their bond portfolio, the fixed outside option α. Banks monitor borrower firms, requiring them to exert a sales effort η, and therefore managers at these firms do not accrue the private benefit B regardless of the actual success if they use external finance. This monitoring comes at a positive cost for the bank, which can be high (c_h) if the firm is "difficult" to monitor or low (c_l) for some technology that facilitates this. Our motivating example is the existence of the more granular and real-time data trail left with Pix compared to the lagging, more aggregate cash flows received by firms from card payments merchants and the bare minimal data associated with cash inflows. Formally, $\Delta c = c_h - c_l = \sigma(\pi_c Q)$ with $\pi_c \neq \pi_q$ another unimportant monotonic parametrisation. In other words, in this model banks care about consumer data trail for two reasons: because it improves the ability of firms to anticipate customer preferences, therefore less likely to default in the first place, and because it makes firms easier to monitor.

All in all, the bank's expected payoff is zero but it can also be calculated as the sum of its expected earnings on the loan amounts, defined as $\hat{R}_b = (p_l + q\Delta p)\beta L$, and the interest earned on the bond portfolio, αT, minus the interest paid to depositors, $\alpha(A_0^* + H_0)$ and the cost of monitoring, $c_h - \Delta c$. The bank only lends if the expected payoff is zero (or greater, which does not happen). Zero is also a natural benchmark for banks as it is the payoff to banks if they do not lend due to the absence of monitoring costs when there is no lending. Since the bond portfolio is the residual bank investment after the lending step, it can be defined as $T = A_0 + H_0 - L$. Manipulating $(p_l + q\Delta p)\beta L + \alpha T = c_h - \Delta c + \alpha(A_0^* + H_0)$ yields:

$$S(L) = \frac{c_h - \Delta c + \alpha(A_0^* + H_0 - T_0)}{(p_l + q\Delta p)\beta}. \qquad 4$$

From equation 4, which governs the supply of loans by banks, we learn that banks loan supply increases when the cost for monitoring is lower, or when the credit risk premium is higher or the firm's performance risk is lower. Recall that $\frac{d\Delta c}{dQ} > 0$. Therefore, banks are more willing to lend when firms have

[12] A non-negative, monotonic parametrisation retains the property that in the absence of data, $Q = 0$, then the guess is as good as random, with a 50% chance of going either way.

[13] Different to Holström and Tirole (1997), we abstract from uninformed investors to focus instead on bank relationships. This is also closer to how the vast majority of firms in Brazil, our empirical setting, obtain external finance.

more customer information due to the easier monitoring. The uniqueness of loan supply suggests that a loan amount L^* exists that equates both endogenous supply and demand for loans[14] as in

$$\frac{c_h - \Delta c + \alpha(A_0 + H_0 - T_0)}{(p_l + q\Delta p)\beta} = \frac{1}{2}\left[\mathrm{A}_0 + \mathrm{q}\Delta\mathrm{pR} - \mathrm{B} + [(A_0 + q\Delta pR - B)^2 - 4(p_l + q\Delta p)\beta]^{\frac{1}{2}}\right]. \quad 5$$

Looking now at households, their expected net income Y comes from firm profits, interest income from their cash deposits H_0, minus retail purchases and any payment fees. Household utility is a function of retail consumption, $u(R)$, with $u(0) = 0, u'(R) > 0, u''(R) < 0$. For brevity, the equation below already simplifies to the case where firms undertake the sales effort:

$$Y = (p_l + q\Delta p)R_f \ + \alpha(A_0 + H_0) - A_p^* - \sum_P C_P(R) - R. \quad 6$$

Note that only retail profit counts toward the household budget, since capital good firms and banks are assumed to be perfectly competitive and therefore have zero profits.

So far, the project gross income R was taken as fixed, but given that it depends on households' payment options, from now on in T0 the firm has a belief $\hat{R}$ about R, which is only revealed in T1. This allows firms to make their decisions with respect to borrowing and attending to customer tastes without really knowing what their actual revenue would be.

3.2 Different payment methods

Now that the main part of the model is defined, another piece that requires a definition relates to the payment methods $P = \{\mathrm{Cash}, \mathrm{Card}, \mathrm{Pix}\}$.[15] They are each uniquely defined as a combination of liquidity effects, data trail and cost (generically, C_P, with $C_{Pix} = 0$). The payment method for the transaction is determined by the preferences of both the firm (P^F) and the customer (P^*) jointly.

Cash, the most traditional payments method, requires the household to have pre-existing liquid funds, $\overline{H_{Cash}} = \mathbf{1}(P_{Cash} \leq H_0)$. The anonymity of cash ensures it leaves a minimal data trail that allow firms to link back sales to specific customers; this is normalised to zero for simplicity: $Q(P_{Cash}) = Q(0)$. And it imposes some cost $C_{Cash} > 0$, associated for example with security requirements or with cash storage (eg, Mariani et al (2023)).

P_{Card} does not require liquid funds and leaves some data trail, $Q(P_{Card}) > Q(0)$. For simplicity in this model card payments are only used transactionally, not as a form of credit (so as to not affect bank balance sheets). This means that when the household uses card, it can decide in T0 to spend up until the sum of its initial cash balance and the expected T1 amount of income: $\overline{H_{Card}} = \mathbf{1}(P_{Cash} \leq H_0 + Y)$. Card payments have *some* ability to follow customers over time, improving over cash on the ability to understand client tastes. The different costs of cash and cards can be interpreted, respectively, as the disutility of using cash such as security considerations or need to withdraw frequently, and as the actual fees but also remuneration to the bank for the credit risk incurred.

Finally, P_{Pix} does require liquid funds, $\overline{H_{Pix}} = 1$, but it leaves a bigger data trail than cards for the same amount, $Q(P_{Pix}) > Q(P_{Card}) > Q(0)$. The cost of Pix can be normalised to zero, reflecting that it is actually zero for households and a comparatively low cost for firms, Duarte et al (2022).

[14] Following the earlier calibration for loan demands, we find banks lending 12% of the project's amount by setting $c_h = 1\%$ of the loan, $\Delta c = 0.5\%$ and $\alpha = 10\%$ (which is high by international standards but in line with Brazilian money markets).

[15] Other payment methods are not modelled here but can be conceptualised as an inner combination of the characteristics of these paradigmatic payment methods.

When the payment method requires the use of cash, households to not earn interest on their balances; alternatively, with the credit card payment method households can earn the deposit yield.

3.3 Equilibrium

The action schedule of the agents in T0 is described below:

Firm chooses $\eta(\hat{\theta})$, $D(L)$ and P^F to maximise equation (2) subject to:

- F.i (*non-negative expected income*): $\left(p_l + \frac{\Delta p(\eta(\hat{\theta})\hat{\theta}+1)(\eta(\hat{\theta}))^2}{2}\right) R_f + \alpha A_0^* - A_p^* + \left(1 - (\eta(\hat{\theta}))^2\right)B \geq 0$;
- F.ii (*external finance incentive constraint for the firm*, from equation 3.ii).

Banks offer loans S(L) to balance their payoff given the competitive lending and deposit markets, subject to the following conditions B.i and B.ii.

- B.i (*monitoring incentive*): $\beta > \alpha$; and
- B.ii (*incentive compatible loan supply*): equation 4 holds.

Households choose payment schedule P (ie, the order in which payment methods are used) and retail consumption R to maximise $u(R^*)$ subject to:

- H.i (*aggregate resource constraint*): $R^* \leq R, R_f^* + R_b^* \leq R^*$;
- H.ii (*cash constraint*): $R > H_0$;
- H.iii (incentive compatibility of consumption): $(p_l + q\Delta p)R_f^* + \alpha(A_0 + H_0 - R(P_{Cash} + P_{Pix})) - \sum_P C_P - R^* \geq 0$.

Definition (equilibrium): The system in equations (1)-(6) is in equilibrium when agents choose $\{\eta, D(L), P^F, S(L), R^*, P^*\}$ in a way that clears in T1 the real market with the expected consumption equating the retail project outcome, $R = R^*$; the demand and supply for loans, D(L) = S(L); and banks' aggregated balance sheet, $T = H_0$; and that no agent (retail firm, bank or household) has an ex ante incentive to deviate.

Proposition (equilibrium): There is a unique equilibrium, defined by conditions E.i-E.iv below.

- E.i (there is only one payment choice): $u(P) > u(P')$ for $P, P' \neq P \in \tilde{P}$.
- E.ii (the firm either undertakes the sales effort or not, and the decision is a function of the payment choices): $\eta \neq 0$ if $\min(R_f, \tilde{R}) \geq B/(q(Q(P))\Delta p)$;
- E.iii (if the second case of E.ii holds, the firm borrows an amount $0 \leq L^* < A_0$: $L^* = D(L) = S(L)$;
- E.iii: $R^* = (p_l + q\Delta p)R_f + \alpha A_0 - \sum_P C_P$
- E.iv: $P^* = P_{Pix}(\min(H_0, R^*)) + P_{card}(\max(0, R^* - H_0))$

E.ii comes from the differences between different payment methods P and the fact that the decision is a threshold action. E.ii says that the firm has a unique level of effort: it either exerts some effort $\eta \neq 0$ or it does not, $\eta = 0$. What determines the level of effort is the (a) probability of success q, itself dependent on the amount of information in the payment choice Q, (b) the expected payoff if successful, R, which is also a function of the payment medium if it is constrained by H_0.

Consider a payment menu $\mathcal{P} = \{Q(P), \overline{H_P}, C_P\}_P$. If the only payment technology is cash, then from H.iii, households can only spend H_0. The firm anticipates this and checks its own incentive F.i with a low (50% - uninformative) customer prediction technology associated with expected payoff $(p_l + 0.5\Delta p)H_0 + \alpha A_0 - A_p^* + \left(1 - (\eta(\hat{\theta}))^2\right)B$. Therefore, whether the firm will make an effort in this situation is dictated by:

$$H_0 \geq \frac{B - A_0 + (1+\beta)L}{0.5\Delta p}.$$

The project is less likely to succeed, as q is smaller due to the absence of data. From equation 4 and the definition of β (which is lower both due to the lower chance of success and potentially from the constrained retail sales amount), the banks will then have a higher hurdle to want to lend, making it harder to supply loans. If the supply of loans is lower than A_0, the firm does not borrow and thus shirking could become a possibility.

A cash-and-card economy, in contrast, relaxes the constraint on consumption but imposes a payment cost, C_{Card}. In turn, it leaves a data trail that facilitates monitoring by banks and increases the probability of success by firms. An equilibrium where households can decide how much to pay in cash and in card has them moving to full on card usage. The rationale is that the data feeds directly into the incentive compatibility constraint, making more projects viable for firms.

Finally, the introduction of Pix would change the model outcome in the following ways. Firms would be even more incentivised to invest, demanding less loans – while banks supply more loans. The retail consumption is not constrained because households also have credit cards that allow households to consume beyond their immediate cash holdings. Since Pix is costless, the household disposable income increases by C_{Cash}. The greater data trail eases the process for banks to monitor the firm (and thus banks are more willing to provide a loan) and for firms to know customers, increasing the odds of success in the retail project. This flows back to households.

3.4 Channels

Since the payment methods differ mainly with respect to their liquidity, data and cost implications, it is now time to define possible channels by which these choices would affect firm external finance outcomes.

Pix's immediate settlement on the firm's accounts, associated with its low cost, increase the resulting A_0 for the same level of R compared to both card and cash (since cash is also costly). The data from Pix allows for less costly bank monitoring of real-time and granular conditions at the firm, compared to the coarser firm-level data from cards[16] and even more from cash. At the same time, Pix offers a clear cost advantage. These relationships are summarised in Table 1 below.

Payment Methods Impact — Table 1

	Firm liquidity	Hard data on firm sales	Cost to merchants
Cash	+	0	+
Card	0	+	+
Pix	+	++	0

Source: Authors.

Considering these differences between payment choices and how they would affect firm outcomes in equilibrium, the following channels could help explain the impact of wider Pix adoption on firms.

[16] Note that cards allow banks to see primarily considerable client-side data *across* retailers, while only as a by-product of client data the bank can extract data related to multiple (or repeated) customers in the same retailer.

Liquidity channel (higher A_0): since Pix settlements are instantaneous, firms might retain some of the cash they received by paying out in less liquid methods. This contrasts with the situation previously, when firms needed to discount card income if they needed liquid funds. From equation (4), an increase in cash assets (ΔA_0) directly *increases the supply of loans* to firms. At the same time, from equation (3.ii), the effect of liquidity in firms' *demand for loans is mixed*: the interval for which firms demand loans increases on both ends, ie both lower and higher amounts are compatible with the firm undertaking its project.

Bank information channel: previously the firm would either receive anonymous cash or an aggregate payment inflow from the card merchant, but now the bank can see all payments coming in real time. The bank sees not just the amounts, but also other valuable information such as the identity of the clients, their purchase values, time of payment, etc. This information could translate into better credit models, helping lenders to extend more (and better priced) loans and to better monitor firm cash flows once a loan has been granted. In the model, this would be represented as a lower monitoring cost, or c, which once again helps *increase loan supply*. Conversely, for firms the data information channel would depend primarily on how much data can help the company better predict customer tastes. While the model foresees such a role in loan demand, in practice for most Brazilian retail firms their scale is not sufficient for data to make a noticeable difference, so we do not posit that this channel will necessarily lead to higher loan demand.

Sales effort channel: The information can also be used by the firm to better estimate customer tastes and increase the chance of success from p_l to p_h. This would be true especially for firms with a bigger number of clients. One story could be that firms now can track users, improving its forecasting activity – for example, firms can now link customer identities to their expenditures without setting up fidelity programmes. But firms might want to match that with stronger sales efforts that try to capture that additional chance of success, converting more customer engagement (from the better matching) into actual sales. Whatever the operational mechanism, firms are more likely to be successful – if not from the data channel, at least from offering a payment method that customers prefer to use. While we do not measure firm success, a proxy that is relevant for external financing is the firm's subsequent credit repayment performance, with the reasonable assumption that more successful firms tend to repay their loans more than less successful ones.

3.5 Confounders

The model underlines unobserved confounding factors that can cloud the identification of the effects of Pix on firm external financing. These are mentioned below.

For one, the unobserved effort choice η introduces a correlation between the firm external financing and the customer expenditure. This creates a correlation between the firm's potential outcomes in terms of lending, which are also determined by this variable, and consumer expenditure. The amount of household deposits and the deposit yield confound the relationship between consumer expenditures and the household incentive to choose one or the other payment method. In yet another example illustrated by the model, from E.ii and E.iii, the firm's payment method decision, its effort level, and bank lending demand are all related to one another, serving as another source of confounding between firm outcomes and the payment method.

Those testable predictions from the model and the empirical strategy to deal with confounders are explored empirically in the next section.

4. Empirical analysis

This section presents the results from our empirical analysis, informed by the model described above and by the following identification strategy. In this paper we are interested in credit outcomes: the availability of credit limits stands in for the supply of credit to firms; actual credit take-up is a proxy for firms' demand for credit; and the repayment performance of the firm is taken as an empirical reflex of the success of its activities.

Collect these three observed variables in W_i, the vector of firm outcomes. Intuitively, W_i can respond to the firm's total income, defined as the sum of all $j \in J$ customers' expenditures on firm i, $R_i = \sum_j R_{ji}$; for example, Drakos and Giannakopoulos (2011) show that firms with higher sales growth or higher profitability undergo less credit rationing. We posit that W_i also responds to the payment method, $P_i = \{(R_i)_p / R_i | p \in \mathcal{P}\}$ where $(R_i)_p$ are the sales amounts received with method p.[17] The goal of this paper is to analyse the effect of Pix on firm outcomes, defined as:

$$\mathbb{E}[W_i | P_i = \text{Pix}]. \qquad 7$$

The effect of Pix on Y_i independent of the amount received by the firm is identified when it is measured across the support of R_i, $\mathbb{E}[W_i|P_i = \text{Pix}] = \int \mathbb{E}[W_i|P_i = \text{Pix}, R_i = r]dr$. Three complications arise in practice. First, the general state of the economy, the cost of credit, the overall tightness of the job market and potentially various other factors influence both R_{ji} and W_i. For convenience, collect the vector of these confounders in U. Second, the payment method is jointly determined by customers and firms, but each side of this decision is potentially influenced by separate unobserved confounders at the customer and the firm levels, respectively termed V_C and V_F. From the customer side, issues like the consumer's bank account liquidity and past credit card performance might plausibly influence their preferred choice method. And from the firm side, a clear connection between the payment method and credit outcomes, if existing, could confound the identification of potential outcomes since the firm might endogenously decide the method that best suits its interest. The third complication is that our data does not include cash sales, potentially biasing naïve estimates due to omitted variables that are correlated with the regressors and the outcome.

This setup is formalised as in Table 2. The first column lists the variables in the model. The second column defines each variable. The third column presents the structural equations in the system. These equations are assumed to fully determine the variables in this system as functions of other variables and of exogenously-determined zero-mean,[18] independent residuals $\epsilon = \{\epsilon_{W_i}, \epsilon_{R_i}, \epsilon_{P_i}, \epsilon_U, \epsilon_{V_C}, \epsilon_{V_F}\} \in \mathbb{R}^6$, where $\{\epsilon_U\}$ affects all firms and customers, and $\{\epsilon_{V_C}, \epsilon_{V_F}\}$ affect customers and the firm outcomes respectively, together with the customer and firm payment preferences. Examples of the factors that might be included in these residuals are discussed in section 3.5.

Econometric model for the effect of Pix on firms' external finance — Table 2

Variables	Definition	Structural equations[1]
W_i	Firm i's credit outcomes	$W_i = f_Y(R_i, P_i, U, V_F, \epsilon_{W_i})$
R_i	Firm i's sales	$R_i = f_C(U, V_C, \epsilon_{R_i})$

[17] Note that while the theoretical model of section 3 results in a single payment method, in practice firms receive their sales proceeds in a variety of methods, and therefore P_i is a vector where each element is the share of sales proceeds received via each payment method.

[18] The zero mean condition can be relaxed without loss of generality.

P_i	Share of each payment method	$P_i = f_P(R_i, V_C, \epsilon_{P_i})$
U	Unobserved[2] confounders of both R_i and W_i	$U = f_U(\epsilon_U)$
V_C	Unobserved[2] confounders of both R_i and P_i	$V_C = f_{V_C}(\epsilon_{V_C})$
V_F	Unobserved[2] confounders of both P_i and W_i	$V_F = f_{V_F}(\epsilon_{V_F})$

[1] Dependence on covariates X_i is omitted for brevity. [2] In this table, "unobserved" refers to variables that are not observed by the econometrician.

Source: Authors.

Note that the sales amount influences the firm's credit outcomes directly and indirectly, through the choice of payment method. The effect of Pix on credit outcomes, which is itself influenced by the sales, can thus be considered as a type of mediation analysis in causal econometrics (Dippel et al (2021)). Specifically, the relationships on Table 2 imply (Dawid (1976), Heckman and Pinto (2024)) that, assuming linear effects, a model that controls for firm income growth and for firm and time fixed effects is able to absorb all confounders. Then, the coefficient on ΔP_i=Pix exactly identifies the effect of Pix on firm outcomes, as in: $Prob(W_i|P_i = Pix\ , R_i, U, V_F)$. This relationship is a reflection of that fact that statistically, firm credit outcomes are independent of the payment method when conditioned on the firm sales (R_i), common confounders between sales and the outcomes (U), partial confounders between the payment method and the outcomes (V_F) and any external hypothetical variation in the payment method, ($\tilde{P}_i$): $W_i \perp P_i|(R_i, U, V_F, \tilde{P}_i)$.

To put concretely, disentangling the effect of Pix on firm external financing requires conditioning these outcomes on the amount earned by the firm *as well* as the unobserved confounders. Using first differences in both the total sales and share of Pix, we further remove potential sources of common confounding.

4.1 Data

Our main dataset relates to electronic payments to firms across various modalities: credit and debit cards, wire transfers, payment stubs, foreign exchange transactions and, from November 2020 onward, Pix.

The core data we use are confidential firm-level monthly panel data of different payment modalities for some 2.8 million retail firms over 2020–3. These modalities include Pix, credit and debit cards, payment stubs and wire transfers; payments made with Pix and wire transfers are only recorded whenever the payer and payee accounts are in different financial institutions. All data mentioned below refers exclusively to these payment types. Unobserved payments include cash, cheque, as well as Pix and wire transfers between accounts in the same financial institution.

Table 2 presents descriptive statistics. Firms had an average of 64 customers in 2023 with a wide variation that reflects the large number of small firms and the much smaller number of large firms. Firms received an average of 118 transactions per month and made an average of 29. On average, firms received monthly payments of BRL 34,500 (USD 5,800) and made payments of roughly the same size – all these numbers with a large variation.

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Descriptive payment statistics in the Brazilian retail sector[19] Table 2

		2020	2021	2022	2023
Number of customers	Mean	2.61	16.16	39.80	64.45
	Median	1	4	9	11
	p25	1	1	1	2
	p75	3	16	36	52
	Standard deviation	58.66	122.37	689.25	1,202.3
Number of transactions received	Mean	5	27.88	70.30	117.90
	Median	2	10	20	25
	p25	1	3	5	6
	p75	5	28	60	87
	Standard deviation	75.27	248.93	1,054.41	1,867.52
Number of transactions made	Mean	5.06	12.65	20.80	28.60
	Median	3	7	11	14
	p25	1	3	4	5
	p75	6	16	25	32
	Standard deviation	7.78	23.77	60.16	145.00
Average ticket per customer	Mean	2,731.32	1,974.04	1,905.07	1,974.56
	Median	240	251.46	234	223.89
	p25	10	64.75	68.33	67.33
	p75	1,021	936.18	844.67	808.57
	Standard Deviation	37,021.18	31,471.90	24,700.85	25,890.96
Amount received (in BRL)	Mean	7,517.61	17,768.73	27,448.07	34,477.86
	Median	450	2,041	3,726.04	4,749
	p25	10.74	216.2	500	668.98
	p75	2,555.26	8,949	14,598.26	18,193.36
	Standard Deviation	161,055.33	287,978.16	450,428.91	703,360.39
Amount paid (in BRL)	Mean	8,921.04	18,550.27	28,108.3	34,522.96
	Median	400	2,550	4,623.31	5,871.06
	p25	0	231	760.24	1,093.9
	p75	3,386.11	10,200	16,414.33	20,162.31
	Standard deviation	155,929.09	346,800.34	520,226.76	762,019.73
Number of observations		983,096	16,950,548	23,741,008	22,188,444
Number of firms		713,120	2,159,234	2,677,325	2,848,233

This table presents descriptive statistics of the variables used in the paper. Values across firms and months. Values from 2020 only includes November and December since it's the period after Pix was launch.

[19] The database provided by the Central Bank of Brazil includes all registered firms that accept Pix payments, excluding those from the informal sector.

4.2 Financial outcomes

We now turn to our empirical analysis to test how a higher amount of firm income coming from Pix payments affects credit-related outcomes. To capture this idea that the effect of Pix on credit is different between supply and demand dynamics, we estimate the following regression in equation (7). In this regression, the dependent variable comprises credit lines (standing in for the supply of loans), actual loan take-up (which represents loan demand) and repayment behaviour (as a measure of the firm's success):

$$\Delta w_{i,t} = \rho \Delta Share\ Pix\ income_{i,t} + \lambda \Delta R_i + \gamma X_{i,t} + a_i + a_t + \varepsilon_{i,t}, \quad 7$$

where the dependent variable $w_{i,t}$ is credit, defined as the log of outstanding credit amount in *reais* of firm i at month t; credit line, defined as the log of credit line in *reais* of firm i at month t, and credit in arrears, defined as the log of outstanding credit amount in arrears above 90 days in *reais* of firm i at month t. $\Delta Pix\ income_{i,t}$ is the firm-level monthly change in the log of Pix income in *reais* + 1 of firm i at month t relative to month t-1. All regressions control for unobserved firm-level effects by including firm fixed effects (FE) directly.[20] $\varepsilon_{i,t}$ is an idiosyncratic error term. We cluster standard errors at the firm level. Vector $X_{i,t}$ controls for a set of observable characteristics of firm i at time t, including the lag of the difference in Pix income, the difference and the lag difference of non-cash incomes. The sample period starts in November 2020 and ends in December 2023.

Table 3 presents the results. Firms with a higher income coming from Pix payments have credit-related outcomes that are consistent with our model. In particular, one percentage point increase in the share of Pix income is correlated to 0.5-1.8% increase in the size of credit limits (columns 1 and 2). This suggests they are perceived to be more creditworthy by lenders, who allow them to borrow a larger amount, all else equal. At the same time, the evidence on actual loan drawdown is mixed but in any case, with a smaller magnitude than loan supply (columns 3 and 4). Finally, the repayment performance improves, as measured by lower credit in arrears (columns 5 and 6), whereas one percentage point increase in the share of Pix income leads to 0.2-1.7% decrease in credit in arrears.

Firms receiving with more participation of Pix payments have higher credit limits and repay more

Table 3

	Credit line		Credit		Credit in arrears	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Pix share in non-cash income	0.018***	0.005***	-0.004*	0.004*	-0.017***	-0.002***
	(-0.003)	(-0.002)	(-0.003)	(-0.002)	-0.004	-0.002
Observations[1]	11.42	11.42	11.42	11.42	11.42	11.42
R-squared	0.083	0.243	0.087	0.193	0.066	0.246
Fixed effect:						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes

[20] Unreported results using location-size-time FEs to control for the bulk of firm-level unobserved variation as in Degryse et al (2019) are broadly consistent with our main results.

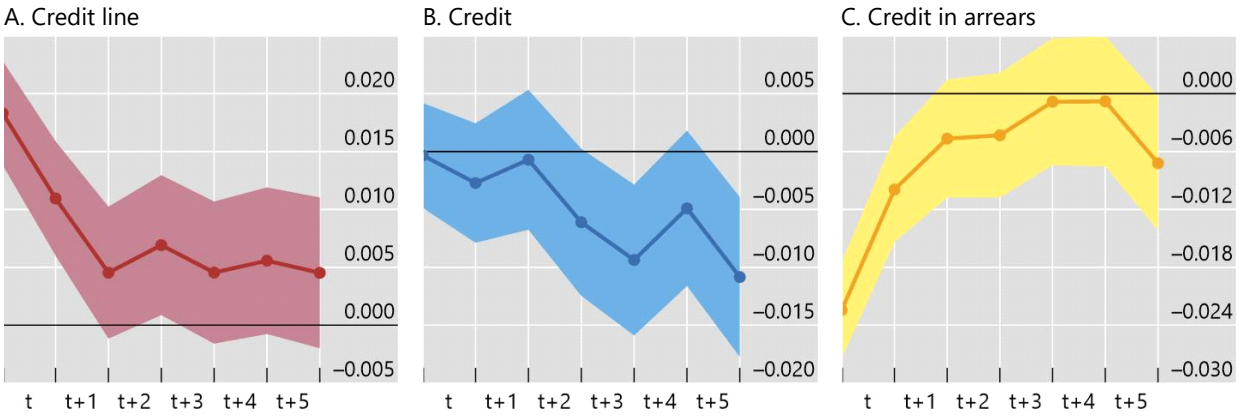
[1] In millions

This tables present the base line specification using as the sample the retail sector in Brazil. The sample period starts in 2020:11 and ends in 2023:12. The specifications account for all firms, where the firm must be present receiving or paying with Pix. Specifications (1), (3), and (5) include controls for lagged values of the percentage change in non-cash total incomes for 6 periods. Specifications (2), (4), and (6) include controls for lagged values of the percentage change in non-cash total income and lagged values of the chance in credit line, credit amount available, and credit in arrears for 6 periods. All regressions are estimated using OLS. All regressions include constant and robust standard errors are clustered on firm level. ***, **, * denote 1%, 5%, 10% statistical significance.

The dynamics of the responses appear to be meaningful, but short-lived. Using local projections (Jordà (2005)) to estimate the duration of the effects (Graph 3), we find that the bulk of loan supply response (left panel) is immediate, with some signs that it may persist somewhat, with a weaker intensity, in the following quarters. Credit (centre panel), in contrast, takes a longer while to respond, but eventually does so in a way that suggests that demand for credit falls. Similarly to credit lines, retail firms receiving a greater share of their income via Pix have an improved repayment behaviour immediately (right panel), before converging to their own normal rates of non-performance, which suggests the improved liquidity from Pix may play a role in firm outcomes.

The Pix effect can be observed in the immediate period, reflecting its impact on the firm's liquidity.

Coefficients[1] Graph 3



[1]The specifications account for all firms in the retail sector, where the firm must be present receiving or paying with Pix. Specification include controls for lagged values of non-cash total incomes for 6 periods. All regressions include constant and robust standard errors are clustered on firm level. Intervals denote 1% significance.

Source: Authors.

But how did this liquidity effect come to be? Since Pix is more used as a payment method by individuals and less so by firms, the net effect would be that firms would more quickly accumulate liquid, instant payments coming in and continue to pay their suppliers with other methods, with some lag. To assess whether this explains the improved liquidity effect from Pix, we regress outgoing Pix payments on incoming Pix amounts (similar to McAndrews and Potter (2002)). Results are presented in Table 4. Here, we show that firms tend to retain a substantial part of their Pix cash inflows, suggesting on average that Pix serves to alleviate financial constraints (Almeida et al (2004)). Growth in outward Pix payments responds positively to contemporaneous and lagged growth in incoming Pix payments, but at low rates. In particular, only 10% of all incoming Pix payments are paid onwards as Pix (of which 7% contemporaneous). Growth in incoming payments in other modalities also increase outpayments via Pix, but in negligible amounts.

These results are robust to different specifications whereby other modalities in received payments are also influencing Pix outpayments, which reinforces the "contemporaneous" channel of Pix incoming payments as a liquidity provider to suppliers. In short, Pix helps firms that receive payments from consumers accumulate some of the liquidity just by virtue of changing the velocity of incoming money with small effect on the velocity of outgoing money. This finding is consistent with corporate finance theory that firms tend to be financially constrained (Almeida et al (2014)).

What happens in Pix stays in Pix

Table 4

	$\Delta\ log$ Pix paid							
$\Delta\ log$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pix income	10.434***	10.101***	10.833***	10.431***	10.844***	10.438***	10.456***	10.132***
	-0.026	-0.027	-0.026	-0.027	-0.026	-0.027	-0.026	-0.026
Cards	0.119***	0.113***						
	0	0						
Bank slip			0.028***	0.026***				
			0	0				
Exports					0.033***	0.032***		
					-0.003	-0.003		
Other revenues							0.112***	0.107***
							0	0
$Lag\ \Delta\ log$								
Pix income	3.791***	3.536***	4.045***	3.738***	4.059***	3.749***	3.779***	3.532***
	-0.02	-0.021	-0.02	-0.021	-0.02	-0.021	-0.02	-0.021
Cards	0.019***	0.017***						
	0	0						
Bank slip			0.010***	0.008***				
			0	0				
Exports					0.016***	0.016***		
					-0.003	-0.003		
Other revenues							0.027***	0.024***
							0	0
Observations[1]	45.92	45.76	45.92	45.76	45.92	45.76	45.92	45.76
R-squared	0.019	0.042	0.012	0.036	0.012	0.036	0.021	0.044
Fixed effect:								
Location	Yes	No	Yes	No	Yes	No	Yes	No
Industry	Yes	No	Yes	No	Yes	No	Yes	No
Firm size	Yes	No	Yes	No	Yes	No	Yes	No
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	No	Yes	No	Yes	No	Yes	No	Yes

[1] In millions.

This table shows the impact of the difference in Pix receivable from firm i in month t – month t-1 on the difference in Pix payments. The sample period starts in 2020:11 and ends in 2023:12. The specifications account for all firms, where the firm must be present receiving or paying with Pix. Specifications (1), (3), (5), (7) and (9) include location, industry, time and firm size fixed effects. Specifications (2), (4), (6), (8) and (10) include firm and time fixed effects. All regressions are estimated using OLS. All regressions include a constant and robust standard errors are clustered on firm level. ***, **, * denote 1%, 5%, 10% statistical significance.

A comparison of incoming and outgoing payments via Pix is, of course, only part of the story. It could be that firms phase out other payment methods that might be more expensive in favour of keeping Pix, or similarly, offer discounts or other advantages that might differentiate conditions for consumers based on how they would pay, therefore pricing some consumers out. The next table checks the influence of Pix incoming payments on the other payment modalities.

Table 5 shows the substitution/complementary effect of Pix income on the other types of income. In column 2 and 3 we can see a substitution effect (below one) of PIX on other revenues. Again, we can also see this contemporaneous channel, as the coefficient of the difference in Pix receivable is much stronger than the one from the lag difference of Pix income.

Pix motivates incoming payments but turbo-charges credit card inflows — Table 5

	$\Delta\ log$									
	Cards		Bank slip		Ted		Exports		Other revenues	
$\Delta\ log$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Pix income	3.513***	3.096***	0.394***	0.284***	1.58	1.2809	0.004**	0.004**	3.592***	3.028***
	-0.017	-0.017	-0.01	-0.011	0.0248	0.0258	-0.002	-0.002	-0.023	-0.023
$Lag\ \Delta\ log$										
Pix income	2.409***	2.134***	0.534***	0.431***	.9388	.6825	0.002	0.002	2.759***	2.346***
	-0.015	-0.015	-0.01	-0.01	0.0232	.0241	-0.001	-0.001	-0.021	-0.021
Cards	-0.213***	-0.240***								
	0	0								
Bank slip			-0.352***	-0.366***						
			-0.001	-0.001						
Ted					-0.4269	-.4362				
					0.000	.0002				
Exports							-0.498***	-0.503***		
							-0.005	-0.005		
Other revenues									-0.334***	-0.355***
									0	0
Observations[1]	45.923	45.76	45.923	45.76	45.923	45.76	45.923	45.76	45.923	45.76
R-squared	0.051	0.097	0.126	0.15	0.1877	0.2059	0.247	0.257	0.118	0.157
Fixed effect:										
Location	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Firm size	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

[1] In millions.

This table shows the impact of the difference in Pix receivable from firm i in month t – month t-1 on monthly difference in Cards, Bank slips, Ted, Exports, and other revenues. The sample period starts in 2020:11 and ends in 2023:12. The specifications account for all firms, where the firm must be present receiving or paying with Pix. Specifications (1), (3), (5), (7) and (9) include location, industry, time and firm size fixed effects. Specifications (2), (4), (6), (8) and (10) include firm and time fixed effects. All regressions are estimated using OLS. All regressions include a constant and robust standard errors are clustered on firm level. ***, **, * denote 1%, 5%, 10% statistical significance.

4.3 Alternative identification strategies

The results in the previous section paint a picture where the payment modality has a noticeable effect on firm outcomes, including access to and use of credit, and repayment behaviour. The introduction and rapid adoption of Pix was the result of top-down decisions, and the roll-out occurred nationwide. For these reasons, coupled with the incentives to use Pix, we see the choice of payment methodology as effectively exogenous to any given firm. But since the share of Pix payments in each firm can be endogenous to a firm's benefit of increased liquidity, we also present results instrumented by variables that shift consumers' propensity to consume or to use Pix regardless of firm characteristics. These findings are broadly consistent with our main set of regressions shown in the previous section.

Our instrument is the level of crime in a given municipality prior to Pix implementation. Different levels of crime might induce individuals to use more Pix (eg to avoid carrying cash, that can be stolen) or less Pix (eg to prevent "lightning kidnappings", in which criminals detain an individual in exchange for ransom), depending on their perceptions. While we do not take a specific stance, there is strong anecdotal evidence suggesting that crime levels might impact consumers' calculations of Pix usage in some way, as well as the overall level of expenditures. For this reason, in this regression we study the effect of the change in Pix income, which is equivalent to multiplying the change in overall firm expenditure and Pix shares.

Data on crime by municipality are obtained from the data platform Base dos Dados (Dahlis et al (2022)). The data are only available in the State of São Paulo. However, because this is the most populous and economically developed state in Brazil, we believe that this exercise is worthwhile for assessing trends for the country as a whole.

Table 6 presents both first stage and second-stage results. First-stage results (column 1) show a strong increase in Pix income by firms in municipalities with high robberies – in line with the idea that greater crime induces firms and/or their clients to use less cash. The second-stage results (columns 2-4) show, once again, that these firms have higher credit lines, lower credit in arrears than their peers that accept less Pix payments.

IV Regression

Table 6

First stage		Second stage			
	Δ log Pix income		Credit line	Credit	Credit in arrears
	(1)		(2)	(3)	(4)
Robberies	.0011**	Effect of Pix	1.299***	0.348	-1.684***
	(.0005)		(0.378)	(0.541)	(0.409)
Δ log		Δ log			
Other revenues	.0247***	Other revenues	-0.014	-0.011	0.019*
	(.001)		(0.009)	(0.009)	(0.010)
Lag Δ log		Lag Δ log			
Other revenues	.0136***	Other revenues	-0.010*	0	0.012**
	(.001)		(0.005)	(0.007)	(0.006)
Observations[1]	23.53	Observations[2]	7.92	7.92	7.92
R-squared	0.175	R-squared	0.001	0.001	0.001

[1] In millions

This tables presents the results of instrumenting the effects of Pix using crime data from the Sao Paulo region. The sample period starts in November 2020 and ends in December 2023. The specifications account for all firms, where the firm must be present receiving or paying with Pix. All specifications include firm and time fixed effects. Results for the retail sector. Robust standard errors in parentheses. Clusters by firm. ***, **, * denote 1%, 5%, 10% statistical significance.

5. Conclusion

Evaluating the impact of fast retail payment systems requires a look beyond the proposition of greater consumer convenience and lower oligopoly rents. As the number and diversity of payments innovations increase, factors such as financial inclusion, the potential effect on effective deposit maturity, and cyber and broader operational resilience of payments infrastructures gain importance. This paper addresses one understudied area where the effects of payments innovations will contribute to this assessment, namely on firm outcomes.

We find evidence for both financial and real effects of Pix on Brazilian firms. On the financial side, firms that receive a higher share of payments via Pix tend to have higher credit limits but to take out smaller loan amounts; crucially, repayment behaviour is also improved. The support for the main results via pre-Pix robbery intensity as instrumental variable lends further credence to our analyses.

There are different ways in which the payments technology itself could affect firms, eg by improving firm liquidity, facilitating sales efforts or by providing more information to lenders. To be sure, while we motivate the empirical analyses with a simple equilibrium model that fleshes out these channels, this paper is not a study of all these effects under equilibrium, so precisely attributing mechanisms to effects or answering questions such as policy counterfactuals would require significant assumptions.

Still, there are lessons to be drawn. First, lenders do seem to differentiate firms whose customers use more vs less Pix, in a way that suggests either a positive effect from the improved liquidity position or on an improved information landscape. The low persistence of these effects suggest a liquidity effect, which is further reinforced as we find evidence that firms retain some of the liquidity received via Pix, paying out with slower-settling methods. These issues appear to deserve closer scrutiny in future research. We hope that the findings we report will trigger further analyses of the effects of payments systems on economic outcomes, leveraging the availability of better and larger datasets.

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Annex

Inside Pix

Pix comprises both a payment infrastructure and a rulebook that governs its functioning. The payment infrastructure includes (i) a real-time gross settlement (RTGS) platform and (ii) a proxy database that facilitates transactions through Pix keys, ie aliases that represent the set of data required to uniquely identify an account. The rulebook lays out the rules upon which the scheme operates and its technical specifications. The BCB has a twofold role in Pix: it develops and operates the infrastructure and determines the rules that govern the system. This is an important feature of Pix which has been recognised as key for overall adoption of fast payments in other jurisdictions (Frost et al (2024)). Among the many detailed rules that drove such high adoption (see also Brandt and Lobo (2021)), two stand out due to their importance in addressing structural market failures such as market concentration and high fees for end users. These are: (i) the rules of participation in the scheme and (ii) the fee structure (Duarte et al (2022)).

Descriptive statistics for the entire economy — Table A1

		2020	2021	2022	2023
Number of customers	Mean	2.20	12.48	27.81	44.37
	Median	1.00	2.00	3.00	4.00
	p25	0	1.00	1.00	1.00
	p75	2.00	9.00	17.00	20.00
	Standard deviation	56.46	1,304.34	3,053.27	5,379.18
Number of transactions received	Mean	4.62	24.14	56.36	108.27
	Median	2.00	6.00	10.00	10.00
	p25	1.00	2.00	3.00	3.00
	p75	4.00	19.00	33.00	39.00
	Standard deviation	108.18	2,939.13	7,847.42	29,172.40
Number of transactions made	Mean	5.45	16.80	23.46	33.77
	Median	3.00	6.00	10.00	12.00
	p25	1.00	2.00	3.00	4.00
	p75	6.00	15.00	24.00	30.00
	Standard deviation	29.41	5,752.76	2,528.93	6,155.68
Average ticket per customer	Mean	5,116.16	4,757.53	5,208.22	5,669.41
	Median	252.93	322.30	346.25	377.75
	p25	0	44.33	60.00	69.41
	p75	1,288.36	1,429.25	1,578.14	1,791.18
	Standard Deviation	166,914.31	134,189.23	170,046.91	195,289.84
Amount received	Mean	12,782.62	25,487.14	37,322.40	46,965.39
	Median	437.40	1,850.00	3,142.21	3,980.46
	p25	0	100.00	247.12	381.44
	p75	2,790.00	8,500.00	12,882.00	15,486.62
	Standard Deviation	539,032.08	837,065.87	1,451,565.30	2,462,367.30
Amount paid	Mean	14,690.6	26,760.50	38,792.50	48,216.41

	Median	551.50	2,588.07	4,248.40	5,053.84
	p25	0	268.90	674.12	900.17
	p75	4,000.00	10,397.17	15,669.66	18,356.47
	Standard deviation	567,952.44	1,047,696.90	1,635,837.00	2,462,116.70
Number of firms		2,463,619	7,674,881	9,906,353	10,962,755
Number of observations		3,391,779	57,766,995	83,392,351	81,527,060

This table presents descriptive statistics of the variables used in the paper. Values across firms and months.

Defining variables

Table A2 gives formal definitions of the variables used in our empirical analysis.

Variable definitions — Table A2

	Description
Credit	Log of outstanding credit amount in *reais* of firm *i* at month *t*
Credit line	Log of credit line in *reais* of firm *i* at month *t*
Credit in arrears	Log of outstanding credit amount in arrears above 90 days in *reais* of firm *i* at month *t*
Pix income	Log of Pix income in *reais* + 1 of firm *i* at month *t*
Pix paid	Log of Pix payments in *reais* + 1 by firm *i* at month *t*
Cards	Log of credit and debit card income in *reais* + 1 by firm *i* at month *t*
Bank slip	Log of boletos (bank slip) income in *reais* + 1 by firm *i* at month *t*
Ted	Log of Ted (Electronic Transfer Available) income in *reais* + 1 by firm *i* at month *t*
Exports	Log of export income in *reais* + 1 by firm *i* at month *t*
Other revenues	Log of the sum of Crt, Bol, Ted and Exports revenues in *reais* + 1 by firm *i* at month *t*
Employees	Log of number of employees of firm *i* at month *t*
Nominal wage	Log of total nominal wages in *reais* paid by firm *i* at month *t*
Minimum wage	Log of total minimum wages in *reais* paid by firm *i* at month *t*
Contractual wage	Log of total contractual salary in *reais* of firm *i* at month *t*
Average wage	Log of average nominal wage in *reais* paid by firm *i* at month *t*
Variable wage	Log of total nominal wage - total contractual salary paid by firm *i* at month *t*
Robberies	Includes the sum of combination of pedestrian robbery, cargo theft, bank robbery, and vehicle theft. It reflects the percentage change in the rate per 100,000 inhabitants during the month preceding the introduction of Pix in the Brazilian economy (Nov 2020). Data for this analysis is available for municipalities in the São Paulo region.

The table presents the definition of variables used in the paper. We use the universe of credit registry, Pix, revenues, and employment information provided by the Central Bank of Brazil for all firms in the country. We also combine this with robbery data for each municipality in the State of São Paulo for the instrument variable analysis.

Additional results

Analyzing the overall economy, Pix supplants traditional bank transfers while significantly boosting credit card inflows

Table A3

	$\Delta\ log$									
	Cards		Bank slip		Ted		Exports		Other revenues	
$\Delta\ log$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Pix income	1.660***	1.460***	0.196***	0.111***	-1.438***	-1.602***	0.010***	0.010***	-0.618***	-0.922***
	((-0.006))	(-0.006)	(-0.005)	(-0.005)	(-0.015)	(-0.015)	(-0.001)	(-0.001)	(-0.014)	(-0.014)
$Lag\ \Delta\ log$										
Pix income	1.251***	1.113***	0.370***	0.288***	-0.644***	-0.792***	0.005***	0.005***	0.359***	0.099***
	(-0.005)	(-0.005)	(-0.005)	(-0.005)	(-0.013)	(-0.013)	(-0.001)	(-0.001)	(-0.012)	(-0.012)
Cards	-0.258***	-0.282***								
	(0)	(0)								
Bank slip			-0.347***	-0.362***						
			(0)	(0)						
Ted					-0.434***	-0.444***				
					(0)	(0)				
Exports							-0.495***	-0.499***		
							(-0.001)	(-0.001)		
Other revenues									-0.391***	-0.408***
									(0)	(0)
Observations[1]	158.30	157.62	158.30	157.62	158.30	157.62	158.30	157.62	158.30	157.62
R-squared	0.069	0.112	0.123	0.149	0.193	0.214	0.243	0.253	0.158	0.191
Fixed effect:										
Location	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Firm size	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

[1] In millions.

This table shows the impact of the difference in Pix receivable from firm i in month t – month t-1 on monthly difference in Cards, Bank slips, Ted, Exports, and Other revenues. The sample period starts in 2020:11 and ends in 2023:12. The specifications account for all firms, where the firm must be present receiving or paying with Pix. Specifications (1), (3), (5), (7) and (9) include location, industry, time and firm size fixed effects. Specifications (2), (4), (6), (8) and (10) include firm and time fixed effects. All regressions are estimated using OLS. All regressions include a constant and robust standard errors are clustered on firm level. ***, **, * denote 1%, 5%, 10% statistical significance.

Using an alternative specification, the history keeps the same: Firms receiving more Pix payments have higher credit limits, borrow less and repay more

Table A4

	Credit line	Credit	Credit in arrears

$\Delta\ log$	(1)	(2)	(3)	(4)	(5)	(6)
Pix income	2.331***	2.053***	0.130***	-0.140***	-3.677***	-3.359***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.022)	(0.022)
Other revenues	0.016***	0.014***	0.000**	-0.002***	-0.023***	-0.020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Lag\ \Delta\ log$						
Pix income	0.759***	0.575***	0.493***	0.239***	-1.291***	-1.118***
	(0.015)	(0.015)	(0.017)	(0.017)	(0.018)	(0.019)
Other revenues	0.007***	0.004***	0.006***	0.003***	-0.009***	-0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations[1]	30.96	30.89	30.96	30.89	30.96	30.89
R-squared	0.002	0.037	0.001	0.040	0.003	0.027
Fixed effect:						
Location	Yes	No	Yes	No	Yes	No
Industry	Yes	No	Yes	No	Yes	No
Firm size	Yes	No	Yes	No	Yes	No
Time	Yes	Yes	Yes	Yes	Yes	Yes
Firm	No	Yes	No	Yes	No	Yes

[1] In millions

This tables present the base line specification using as the sample the retail sector in Brazil. The sample period starts in 2020:11 and ends in 2023:12. The specifications account for all firms, where the firm must be present receiving or paying with Pix. Specifications (1), (3), and (5) include location, industry, time and firm size fixed effects. Specifications (2), (4), and (6) include firm and time fixed effects. All regressions are estimated using OLS. All regressions include a constant and robust standard errors are clustered on firm level. ***, **, * denote 1%, 5%, 10% statistical significance.

Similar results hold including all sectors in the economy

Table A5

	$\Delta\ log$					
	Credit line		Credit		Credit in arrears	
$\Delta\ log$	(1)	(2)	(3)	(4)	(5)	(6)
Pix income	1.868***	1.694***	-0.139***	-0.324***	-2.640***	-2.451***
	(-0.007)	(-0.007)	(-0.008)	(-0.008)	(-0.009)	(-0.009)
Other revenues	0.014***	0.012***	-0.004***	-0.005***	-0.016***	-0.014***
	(0)	(0)	(0)	(0)	(0)	(0)
$Lag\ \Delta\ log$						
Pix income	0.574***	0.456***	0.257***	0.084***	-0.921***	-0.816***
	(-0.007)	(-0.007)	(-0.008)	(-0.008)	(-0.008)	(-0.008)
Other revenues	0.005***	0.003***	0.002***	0	-0.006***	-0.006***
	(0)	(0)	(0)	(0)	(0)	(0)
Observations	98,553,899	98,258,926	98,553,899	98,258,926	98,553,899	98,258,926
R-squared	0.002	0.038	0.001	0.042	0.002	0.026
Fixed effect:						
Location	Yes	No	Yes	No	Yes	No
Industry	Yes	No	Yes	No	Yes	No
Firm size	Yes	No	Yes	No	Yes	No
Time	Yes	Yes	Yes	Yes	Yes	Yes
Firm	No	Yes	No	Yes	No	Yes

This table shows the impact of the difference in Pix receivable from firm *i* in month *t* – month *t-1* on credit line, credit and credit in arrears. The sample period starts in 2020:11 and ends in 2023:12. The specifications account for all firms, where the firm must be present receiving or paying with Pix. Specifications (1), (3) and (5) include time, location and firm size fixed effects. Specifications (2), (4) and (6) include firm and time fixed effects. All regressions are estimated using OLS. All regressions include a constant and robust standard errors clustered on firm level. ***, **, * denote 1%, 5%, 10% statistical significance.

Exploring alternative identification strategies within the entire economy

Table A6

First stage		Second stage			
	Δ log Pix income		Credit line	Credit	Credit in arrears
	(1)		(2)	(3)	(4)
Robberies	.0012**	Effect of Pix	0.602***	0.248	-0.862***

	(.0006)		(-0.222)	(-0.305)	(-0.243)
Δ log		Δ log			
Other revenues	-.0046***	Other revenues	0.016***	-0.005***	-0.018***
	(.0003)		(-0.001)	(-0.001)	(-0.001)
Lag Δ log		Lag Δ log			
Other revenues	.0045***	Other revenues	0.002**	0	-0.003**
	(.0003)		(-0.001)	(-0.001)	(-0.001)
Observations[1]	23.97	Observations[2]	27.98	27.98	27.98
R-squared	0.0025	R-squared	0.001	0.001	0.001

[1] In millions

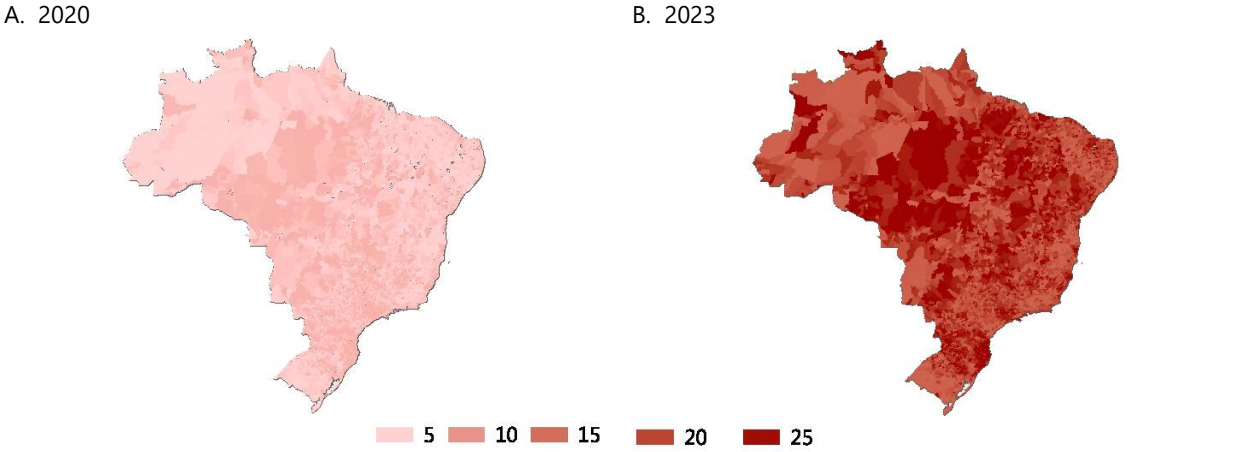
This tables presents the results of instrumenting the effects of Pix using crime data from the Sao Paulo region. The sample period starts in November 2020 and ends in December 2023. The specifications account for all firms, where the firm must be present receiving or paying with Pix. All specifications include industry, firm size and time fixed effects. Robust standard errors in ( ). Clusters by firm. ***, **, * denote 1%, 5%, 10% statistical significance.

Visualising changes in Pix use

Pix use has taken off during the sample period. Graph A1 shows that the number of firms that accept Pix payments rose rapidly, to 25% and higher in many municipalities in 2023.

Number of firms that accept Pix payments[1]

In per cent — Graph A1



[1] Number of firms that accept Pix payments reported at the end of the year, divided by the total number of firms for each municipality.

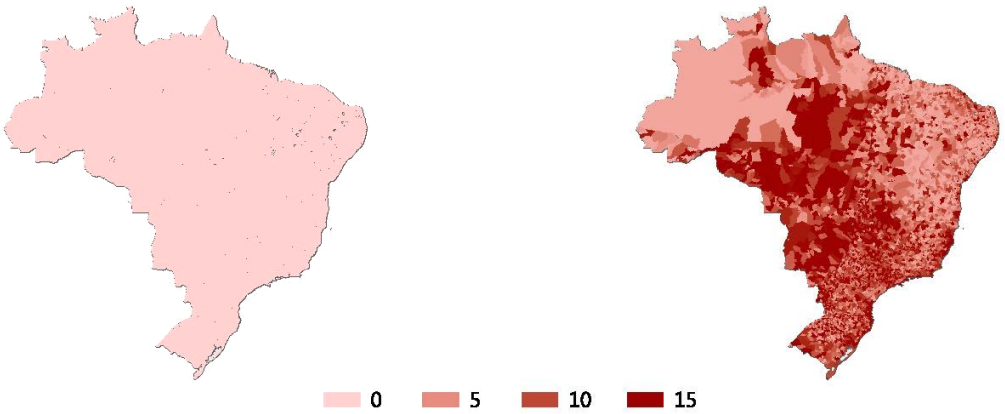
Source: Central Bank of Brazil; BIS.

Relatedly, firms saw a rapid increase in Pix transactions received (graph A2). The number of transactions per firm was particularly high in municipalities in the interior of Brazil.

Pix transactions received

Number of transactions[1] Graph A2

A. 2020 B. 2023



[1] Numbers of firm transactions received by firms per municipality. Cumulative values for the entire period, divided by the population of each municipality.

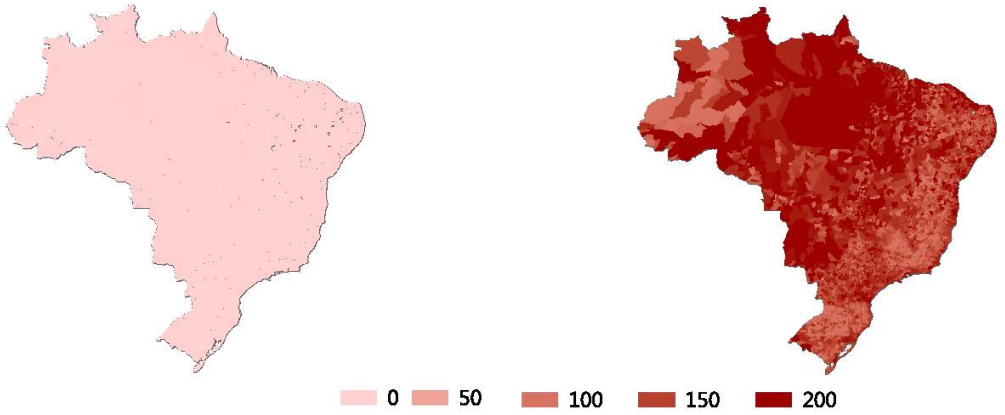
Source: Central Bank of Brazil; BIS.

Firms also made an increasing number of payments with Pix themselves (graph A3). This is widespread across the country, including the relatively poorer North and Northeast.

Pix transactions made

Number of Pix transactions[1] Graph A3

A. 2020 B. 2023



[1] Number of Pix transactions made by firms per municipality. Cumulative values for the entire period, divided by the number of firms in each municipality.

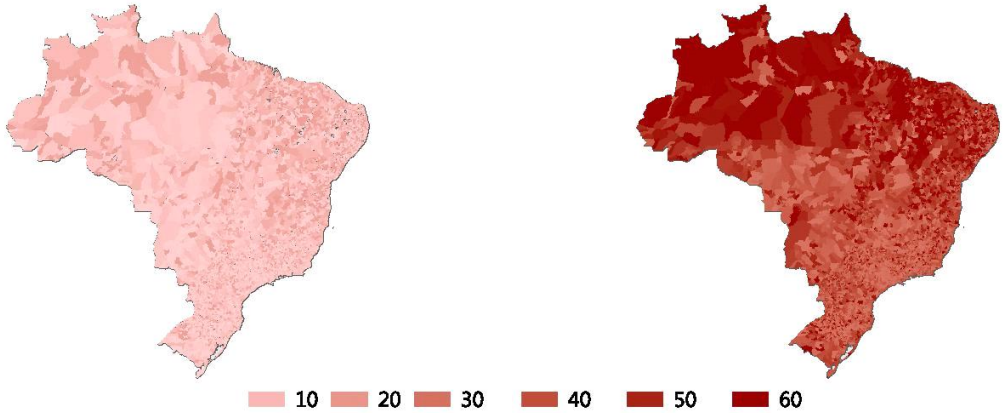
Source: Central Bank of Brazil; BIS.

Pix income became the majority of revenues for the average firm in a number of municipalities in Brazil (graph A4). Again, it is notable that this share is higher in the North and Northeast of the country.

Pix income to total measured revenues

In per cent[1] Graph A4

A. 2020 B. 2023



[1] Percentage of revenue via Pix relative to the total revenue of firms. Cumulative values for the entire period by municipality.

Source: Central Bank of Brazil; BIS.