Banks' Physical Footprint, Digital Payment Technologies, and Fintech Growth

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Abstract

Does the diffusion of digital payment technologies enable fintechs to become more competitive and expand? Does the branch network of traditional banks moderate the usage of these technologies? To answer these questions, we leverage unexpected bank heists that involve the use of explosives and disrupt branches' short-term capacity to supply cash services. These incidents are unrelated to local crime trends, and even though affected branches restore their supply capacity, they lead to persistent increases in digital payments usage. We show that this digitalization boost paves the way for digital institutions' growth not only in payment but also in credit markets.

Keywords: Technology adoption, Payment methods, Credit, Fintechs

JEL Classifications: E42, E51, G20, O33

1 Introduction

The emergence of fintech firms and the proliferation of new technologies have been transforming the financial industry. These developments are prompting traditional financial services providers to reduce their physical footprint and increase the provision of digital services.[1] One of the potential benefits of these changes is increased competition in the banking industry (e.g., Philippon 2018; Vives 2017, 2019).

In this paper, we focus on digital payment technologies and delve into how they can alter the banking market structure. We leverage a shock that temporarily impairs the cash service infrastructure of bank branches and prompts a locality to permanently reduce its reliance on cash in favor of digital payment methods. We then use this rise in digitalization to document a channel through which digital payment technologies can enhance competition: they allow digital institutions that do not operate through a physical branch network to expand in *both* payment and credit markets.

A key function of physical bank branches is the provision of payment services, especially through the storage and distribution of currency. The attractiveness of cash as a means of payment increases in the vicinity of branches due to lower costs of making withdrawals and deposits. Since payment methods display adoption complementarities, coordination failures can arise and impede the penetration of alternative technologies (e.g., Crouzet et al. 2023; Higgins 2024). Moreover, learning costs, lack of trust, organizational constraints, behavioral biases, and informational barriers can also hinder the adoption of new methods (e.g., Breza et al. 2020). Therefore, individuals and firms with easy access to a branch can continue to use cash even when new, welfare-enhancing payment technologies become available. Such reliance on cash reduces the competitiveness of institutions that only operate digitally and do not have the physical infrastructure to support cash deposits and withdrawals. In the presence of scope economies between payment and credit services, digital institutions might see nega-

[1] The number of full-service brick-and-mortar branches in the United States decreased from 83,236 in 2016 to 75,674 in 2021 (FDIC 2022). In Brazil, the number of branches decreased from 22,547 in 2016 to 17,644 in 2021.

tive spillovers from local cash dependence to their competitiveness in credit markets (Basten and Juelsrud 2023; Gambacorta et al. 2023; Ghosh et al. 2023).

We explore the consequences of unexpected shocks that disrupt branches' short-term capacity to supply cash services and increase cash handling costs. In general, the suspension of branch services results from banks' operating decisions and can reflect unobserved factors that also determine technology adoption. For instance, banks might close branches where the population is more likely to use digital services (Jiang et al. 2022). We address endogeneity concerns by focusing on a shock caused by criminal activity that leaves branches temporarily inoperable. We show that such events have lasting effects on the usage of digital payment technologies and that when a locality depends less on cash, digital financial institutions grow in payment and credit markets.

The criminal activity we explore is a bank heist in which criminals use explosives to access all the cash stored in the vaults and ATMs of branches. The attacks happen in the dead of night when the streets are empty and there is less police presence. They have a "hit-and-run" feature, as immediately afterward, the group flees the region. Their usual fallout is the partial or total destruction of the establishment and the interruption of cash services for a couple of months. The abrupt suspension of these services has adverse consequences, especially in localities with few bank establishments, which are the majority in Brazil, as the median municipality has only two bank establishments. In these locations, criminals generally target all the branches, which forces individuals to travel long distances to access cash, reducing its appeal as a means of payment.[2]

These heists require skilled personnel, meticulous training and planning, and expensive apparatus. The criminals belong to *non-local* organized crime syndicates, and the raids are not associated with increases in other criminal activities or changes in local unobserved variables that could correlate with financial technology usage decisions. These features make the setting particularly well-suited for answering the research questions we pose. Leveraging weekly and monthly data, we implement an

[2]See, for instance, the Reuters article *Exploding ATMs: Brazil banks wrestle with dynamite heists* (link).

event-study difference-in-differences empirical strategy around these criminal events using unaffected municipalities as a control group.

We first show that the shock has a large impact on the amount of cash stored at the targeted municipalities' branches. Compared to control municipalities, this quantity drops by 32% in treated municipalities. In treated municipalities with at most two bank establishments (median), the cash inventory drops by 94.5%.[3] Since banks did not offer the service of storing valuables to customers during our sample period, the cash inventory refers to banknotes and coins used for transaction purposes. Moreover, most ATMs are located inside branches due to security concerns. Therefore, these results imply that cash services experience severe disruption in the immediate aftermath of the shock in municipalities with a limited number of bank establishments. As banks refurbish branches and resume the provision of cash services, the stock of cash starts to grow in treated municipalities, and one year after the shock, it returns to pre-robbery levels. However, in comparison to the counterfactual trajectory of control municipalities, treated municipalities operate with less cash even twelve months after the robbery, suggesting that a short-lived supply shock can change the demand for cash in the long run.

We show that, regardless of the number of bank establishments in the municipality, these crimes have no impact on the deposits of branch-based banks, indicating that the main consequence of the robberies is the impairment of cash services. We then investigate whether branch explosions and local criminal activity are connected. We show that the shocks are neither followed nor preceded by an increase in homicides, supporting the hypothesis that such events are uncorrelated with trends in local crime and attenuating concerns that the drop in cash usage is driven by individuals becoming fearful of carrying cash.

We study the implications for the usage of digital payment technologies, focusing on Pix, an instant payment system launched by the Central Bank of Brazil. Pix is free to individuals, user-friendly, available 24/7, and only requires a bank account and internet

[3]The magnitude of the effect decreases monotonically with the number of bank establishments in the municipality.

connection. Users access Pix through banks' mobile apps or websites. We focus on intra-municipality transactions, as these are more likely to be substitutes for cash. In municipalities with at most two bank establishments, where cash services are severely disrupted, we observe a 24.5% increase in the number and a 15.8% increase in the value of intra-municipality Pix transactions in the twelve months following robberies. The dynamics of these effects show that Pix usage grows for roughly two months post-event and remains higher thereafter. Pix usage increases among individuals both as payers and payees, whereas firms show an increase only as payees, consistent with cash not being the primary method for business-to-business transactions prior to the shock. We observe no change in Pix utilization in municipalities with more than two bank establishments, where cash services are less disrupted.

The contrasting outcomes in regions with severe versus mild cash services disruptions indicate that, in the immediate aftermath of the shock, the increase in Pix usage is primarily driven by the unavailability of cash services rather than a shift in cash demand related to security concerns arising from the robbery. However, the persistence of the effects even when the cash services infrastructure is restored indicate that temporary spikes in cash handling costs translate into a larger demand for digital payments over the long run.

We then document spillovers for institutions operating in treated municipalities but not directly attacked, including non-targeted branch-based banks and digital institutions. In contrast to cash transactions, Pix transactions are recorded by both payers' and payees' banks. Moreover, digital institutions provide more transaction convenience when the residents of a locality jointly replace cash with non-physical methods. Consequently, the digitalization boost from the robbery should impact unaffected institutions, especially digital ones. We find that the number and value of Pix transactions increase for unaffected institutions after a bank robbery in the municipality, compared to their counterparts in control municipalities. In general, digital institutions experience larger spillovers than unaffected branch-based banks. Moreover, unlike unaffected branch-based banks, digital institutions experience growth across all Pix utilization measures we test: number and value of Pix transactions of individuals and firms as payers or payees.

These spillover effects are not limited to payment services: unaffected institutions also provide more credit after the shock. Nevertheless, unlike payment spillovers, which impact both unaffected branch-based banks and digital institutions, credit spillovers are confined to digital institutions. We show that the amount of household loans originated by digital institutions increases by 21% in treated municipalities relative to their counterparts in control municipalities. We also observe that digital institutions increase their business credit provision by 77.5%.[4]

We examine potential channels through which credit spillovers materialize. We show that these spillovers are driven by loan types in which digital banks specialize and for which transaction data is a key input in the credit origination process: unsecured, information-sensitive loans. For collateralized loans, not only credit spillovers for digital banks do not exist but also targeted banks are not affected. These results provide evidence that the short-term disruption in the branch does not affect its capacity to grant loans in the twelve months following the robberies. Digital banks benefit from the shock because of digital payments spillovers and supply complementarities between unsecured credit and payment services.

Finally, by exploiting the fact that our sample period includes pre- and post-Pix periods, we provide suggestive evidence that Pix amplifies the credit spillover effects.[5] In the pre-Pix period, we document an increase in debit and credit card usage after robberies. However, these methods are more expensive and their scope is more limited, as they cannot be used for person-to-person or business-to-person transactions. We find that the increase in digital institutions' household credit is three times larger after Pix's introduction. Moreover, digital institutions' business loans only increase in the Pix period. Overall, our results show that cash dependence limits digital institutions' ability to provide payment services. The removal of barriers to entry in payment mar-

[4]The large magnitude is due to the small participation of digital banks in the business loans market. In 2021, their share in the stock of credit to firms was 0.59%.

[5]Results are indicative as they can be biased by aggregate time-varying confounders. For instance, the migration to fintechs might be stronger post-Pix because of stronger brand recognition and reputation.

kets and the availability of an inclusive digital payment method allow these firms to exploit their comparative advantages in lending, such as a more effective utilization of transaction data.[6]

Our paper ties into the literature that documents the benefits that new payment technologies can bring to consumers and firms.[7] We focus on how these technologies can promote a level playing field in banking, particularly by reducing the entry and fixed costs of providing payment services related to the storage, distribution, and transportation of cash.[8] Sarkisyan (2023) analyzes how higher COVID-19 incidence affected Pix usage and its consequences for competition in the deposits market among traditional, branch-based banks. We explore a different source of variation and highlight the effects of payment digitalization on competition by focusing on fintech growth in payments and credit markets. Digital banks are the fastest-growing type of financial institution and important candidates to thrive when payments digitalize, since they do not possess a cash service infrastructure. The fact that credit spillovers are limited to these institutions also indicates that they are better positioned to leverage the availability of transaction data (e.g., Babina et al. 2024, Berg et al. 2022).

Our paper connects to recent literature investigating the determinants of digital payment technology adoption. Payment technologies exhibit network externalities, causing coordination failures that hinder the diffusion of new technologies (Alvarez et al. 2022; Buera et al. 2021; Katz and Shapiro 1986; Rochet and Tirole 2006). Additionally, fixed adoption costs, behavioral biases, and lack of trust and information can also impede adoption (e.g., Bachas et al. 2018; Breza et al. 2020). Events that temporarily increase the cost of using one payment technology can lead to the joint and permanent

[6] Ghosh et al. (2023) show that fintechs utilize transaction data to assist the credit origination process. These data play a particularly important role in the provision of information-sensitive loans (Gambacorta et al., 2023). See also Babina et al. (2024), Berg et al. (2022), and Ouyang (2021).

[7] Payment technologies can affect transaction costs (Bachas et al. 2018), savings (Bachas et al. 2020), consumption (Agarwal et al. 2024), risk-sharing (Jack and Suri 2014; Riley 2018), availability of hard information and credit access (Dalton et al. 2023; Ghosh et al. 2023; Parlour et al. 2022), occupational choice and labor reallocation (Suri and Jack 2016), business creation and growth (Beck et al. 2018); and crime and tax evasion (e.g., Alvarez et al. 2021).

[8] More generally, digital technologies (e.g., mobile apps) can change other sources of market power, such as search and switching costs. Koont (2023) shows that mid-sized banks grew more during the digital disruption in banking.

adoption of an alternative one (Chodorow-Reich et al. 2020; Crouzet et al. 2023; Higgins 2024).[9] Our study examines how the physical footprint of banks influences the spread of new technologies, highlighting the role of branches in facilitating cash use and interfering in the digital transition.[10]

This paper also builds on the literature that studies the consequences of interruptions of branch services. Bonfim et al. (2021) and Nguyen (2019), among others, document negative effects on credit for clients directly exposed to a branch closure. We add to these papers by studying how the suspension of branches' cash services can be a catalyst for the spread of digital technologies and how digital payments can help mitigate the negative effects of these disruptions. Additionally, by documenting spillovers to unaffected institutions, we expand upon previous literature that analyses the effects of disruptions to banking services on technology adoption within a specific financial institution (e.g., Choi and Loh 2023). By finding results on credit, we also contribute to the literature that studies supply and demand complementarities between credit and payment services (e.g., Basten and Juelsrud 2023; Benetton et al. 2022; Ghosh et al. 2023). Finally, structural models of the banking industry highlight the role of branches and ATM networks as a source of barrier to entry and product differentiation (e.g., Dick 2008; Gowrisankaran and Krainer 2011; Xiao 2020). We shed light on the role of these networks in slowing down the adoption of new payment technologies that face more competition from digital rivals.

[9] Regarding the adoption of Pix, Barros et al. (2023) show how natural disasters spark its adoption.

[10] As access to new technologies remains unequal, our results also show that, by facilitating the use of cash, branches still play an important role (Alvarez and Argente 2022; Jiang et al. 2022; Saka et al. 2022).

2 Empirical Setting

2.1 The Banking Industry in Brazil

The financial industry in Brazil is concentrated.[11] The five largest commercial banks accounted for 78.2% of the assets and 80.5% of the total credit in 2016. Despite a reduction in recent years, the same measures remained large in 2022 (assets, 65.4%; credit, 71.2%).[12] In the same year, the fee income of the five largest commercial banks amounted to 76.2% of all fees levied in the financial system.

The banking industry has been digitalizing and reducing its physical footprint. The number of branches dropped from 22,547 in 2016 to 16,737 in 2023, a 26% reduction. Part of the reduction in the number of branches was offset by an increase in service stations. Service stations are establishments with simpler and cheaper structures. For instance, they do not need a vault, security (guards, metal detector), and certain employees (treasurer, bank teller). Therefore, they provide fewer payment services, especially large cash transactions. However, small-value cash operations can be carried out at ATMs inside these stations, and loan officers can grant credit as in a standard branch. Therefore, throughout the paper, we treat these service stations as standard branches. The share of municipalities with neither a branch nor a service station increased from 6.7% to 8.6% between 2016 and 2021.

The digitalization trend is reflected in the customer channels that are more frequently used to perform transactions. In Table A1 of the Online Appendix, we show that, in 2020, transactions using the internet or mobile banking accounted for 53.7% of all transactions, followed by ATMs (23.8%), retailers serving as bank agents (11.2%) and branches (9.2%). The most common transactions carried out at branches (but not including ATMs inside them) are the payment of invoices (22.3%), followed by

[11] A high level of concentration is common in this industry. In a sample of 123 countries, the average share of assets held by the 5 largest banks was 80.4% in 2021 (World Bank Global Financial Development Database).

[12] Reference dates: December 2016 and September 2021. The sample excludes the national development bank (*Banco Nacional de Desenvolvimento Econômico e Social*, BNDES) and includes all financial institutions that grant loans, including credit unions and non-deposit-taking lenders.

the issuance of statements/balance checks (14.4%), credit transfers (11.4%), deposits (10.7%), loans (8.9%) and cash withdrawals (7.2%). Cash withdrawals are the most common transaction in ATMs (38.7%), followed by the issuance of statement and balance checks (35.8%). Branches account for 51.6% of all loan transactions, 22.9% of all credit transfers, and 20.5% of all deposit transactions, while ATMs are responsible for 79.3% of all cash withdrawals transactions and 50.8% of all deposit transactions. As the majority of ATMs are located inside branches due to security concerns, the temporary closure of a branch can be very disruptive, increasing the costs of cash withdrawals and deposits and, at the same time, increasing the costs of monitoring balances and applying for loans.

New firms that rely exclusively on digital customer channels have entered the banking sector in recent years. In Figure A1 of the Online Appendix, we show the growth in the number and market share of these institutions. In 2018, out of 1,186 active financial institutions, 6 were digital; in 2022, out of 1,119 financial institutions, 66 were digital. We show that these firms specialize in credit to individuals (Panel B): in 2022, their market share in the stock of credit to individuals was 3.7%, while their participation in the stock of credit to firms was 0.8%. Their share of deposits grew from 0.6% in 2018 to 4.4% in 2022. Among loans to individuals, digital banks specialize in unsecured loans (Panel C): in 2022, their market share in credit card debt was 13.7% and in personal loans 8.3%; in contrast, their participation in mortgages and auto loans was 0.5%.

2.2 The Introduction of Pix

In November 2020 the Central Bank of Brazil launched a new instant payment system called Pix.[13] Pix allows payments from all types of accounts and is available 24/7. It is a real-time gross settlement payment system. Pix transfers can be carried out based on a simple key (email, ID, or phone number) or QR code instead of relatively lengthier bank account details. To perform a transaction, users only need an account at a bank or payment institution and a connection to the internet.

[13]For more information about the Pix structure, see https://www.bcb.gov.br/en/financialstability/spi_en, Duarte et al. (2022), and Lobo and Brandt (2021).

Pix has two distinctive regulatory features: (i) the participation of institutions with more than 500,000 active customer accounts is mandatory; (ii) individuals do not pay set-up or transaction fees to receive or send money. The mandatory participation of large banks and the absence of fees for individuals aimed at promoting Pix usage and adoption. Before Pix, the options were costlier (less inclusive), less user-friendly, and not instant.

Between its launch and December 2021, 96 million individuals (54% of the adult population) made at least one transfer using Pix (Central Bank of Brazil 2021). In Table A2 of the Online Appendix, we report that more than 9 billion Pix transactions were made in 2021, totaling more than BRL 5 trillion (around USD 1 trillion). Regarding the number of transactions, Pix was particularly successful among individuals, with person-to-person and person-to-business transactions representing 62.3% and 11.9% of the total number of transactions, respectively. Pix is particularly popular among young individuals: those between 20 and 40 years old account for more than 60% of the transactions in which a person is a payer. Regarding the value transacted, person-to-person transactions represent 36.3% of the total, followed by business-to-business transactions (30.5%). Despite its success, around 71 million adults (40% of the adult population) still did not use any electronic system to make transfers in December 2021 (Central Bank of Brazil 2021).

Before Pix, the main means for individuals and firms to transfer resources were credit, debit, and pre-paid cards, checks, an electronic credit transfer option known as TED (*transferência eletrônica disponível*), and a payment order known as *boleto*. The most similar option to Pix is a TED transfer, which both firms and individuals can use. It takes from a few seconds to a few hours to clear and can be carried out only during business hours on business days. A *boleto* is a payment order or invoice (physical or digital) issued by a bank on behalf of a firm. The order contains a bar code, which is the only information needed to make the payment. In Table A3 of the Online Appendix, we show that Pix quickly gained importance as a payment method. In 2021, a little over a year after its launch, Pix accounted for 15% of the number of transactions, while debit cards accounted for 21.2% and credit cards 20.1%.

In Table A4 of the Online Appendix, we show how local characteristics correlate with measures of Pix usage per inhabitant. Municipalities that use more Pix per inhabitant (both in terms of quantity and value) have a higher GDP, GDP per capita, and internet access; their economies rely more on the manufacturing and services industries. In terms of financial sector characteristics, municipalities with higher Pix usage per inhabitant have more deposits and branches.

In Panel D of Figure A1 of the Online Appendix, we show that digital banks are important providers of Pix payments, especially for individuals. In 2022, roughly 45.9% (39.9%) of the registered Pix keys/aliases of individuals (firms) were associated with accounts in digital banks.

2.3 Bank Robberies

Brazil has suffered from attacks by organized crime gangs that use explosives and/or blowtorches to access the cash stored inside branches' ATMs and vaults. The raids occur in the dead of night, and, shortly after the action, the criminals flee the targeted city. In general, the heist destroys the entire branch (Figure 1), which needs to be refurbished to become operable again.

The raids are carried out by sophisticated crime syndicates that are composed of members from different regions and operate in large swathes of the country. They require skilled personnel, careful planning, and expensive equipment. According to Sao Paulo's Anti-Bank Robbery Task Force, the costs of performing a raid can reach BRL 400,000 (around USD 80,000), and a typical heist requires the participation of at least 10 people.[14] The complexity and high cost of these operations imply they are unlikely to be carried out by local, less sophisticated criminals. This is appealing for our identification strategy since raids are unrelated to trends in other crimes. We formally test this claim in Section 4.2.

We collect data on robberies in 18 states between 2018 and 2021. Our sample con-

[14]See the Reuters article *Exploding ATMs: Brazil banks wrestle with dynamite heists* (link).

tains 1,134 robberies that destroyed branches. These robberies happened in 714 municipalities.[15] The states in our sample account for 88% of the municipalities (4,878 out of 5,570), 93% of the branches, and 91% of the national GDP in 2019. The number of robberies has fallen over time: 659 in 2018, 241 in 2019; 121 in 2020; and 113 in 2021.

2.4 Data

We combine data from several sources to obtain information on robbery events, the operation of physical branches, payment technology adoption, credit usage, and fintech penetration at the municipality level.

Bank robberies. We build a novel dataset with information on bank robberies, including whether criminals use explosives and the extent of damage to the branch. The explosion of branches receives ample attention from media outlets and is recorded by state police departments. We follow two complementary methods to construct the dataset. First, we requested information on robbery events from state police departments. When state police departments' records do not contain data on the identity of the banks that were robbed and whether the criminals used explosives and the establishment was destroyed, we search the internet to obtain the information. As we do not observe robberies that happened before 2018, to maximize the likelihood that the robbery event in our sample is the first one the municipality is experiencing, we exclude municipalities that had robberies on two different dates during our sample period. These municipalities tend to be larger in terms of population, geographical area, number of bank facilities, and GDP (Table A5 of the Online Appendix). For example, the city of Rio de Janeiro experienced the destruction of 23 bank establishments between 2018 and 2021. Therefore, it is unlikely that the first event in our data was the first time a branch was destroyed in this municipality. After this filter, the number of robbed municipalities becomes 578.

Bank branch information. The Central Bank of Brazil maintains a dataset on

[15]The criminal group might explode more than one branch on the same night or the same municipality might be targeted on different dates, hence the number of robberies being larger than that of municipalities.

physical bank branches (*Estatística Bancária Mensal*, ESTBAN). The data contain the branches' municipality and monthly balance sheet information, including the stock of deposits and cash inventory. This dataset does not contain information on service stations and digital institutions. As banks in Brazil do not provide customers with safes for the storage of money, we use the cash inventory as a proxy for the amount of transaction cash services the branch provides.

Pix. The Central Bank of Brazil maintains data on Pix transactions. The data contain information on the transaction date, value, payer's and payee's characteristics (firm or individual, municipality), and payment service provider (PSP). Even though a Pix PSP can be either a bank or a payment institution, we refer to Pix PSPs as banks for simplicity. We collect Pix weekly information at the municipality and municipality-bank levels. We classify banks into two types:

- *Branch-based banks*: commercial banks that have physical branches;
- *Digital institutions*: institutions that rely exclusively on digital services. These include digital commercial banks and payment institutions.

We do not observe Pix transactions between accounts of the same institution. Nevertheless, this is a relatively small fraction of total Pix transactions. We exclude Pix transactions between accounts that belong to the same person or firm.

Credit. The Central Bank of Brazil also maintains a credit registry (*Sistema de Informações de Créditos*, SCR), which contains data on the universe of bank loans above 200 BRL (around 40 USD). With this dataset, we build a panel with credit information at the municipality-bank-month level. We observe whether the borrower is a firm or individual, and the loan type.

Municipality characteristics. We collect municipal data from several sources. We obtain population, geographical area, and GDP information from the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatistica*, IBGE). We collect homicide data from the Ministry of Justice and access to internet data from the Brazilian telecommunications regulator (*Agência Nacional de Telecomunicações*, Anatel).

2.5 Empirical Strategy

Our empirical strategy consists of difference-in-differences event-study regressions in which we exploit quasi-experimental variation arising from bank heists. Our identification assumption is that treated and non-treated municipalities would follow parallel trends had the robberies not occurred. Although ex-ante heterogeneity does not necessarily invalidate the method, we implement a Coarsened Exact Matching (CEM) technique to obtain a more balanced sample (Blackwell et al. 2009).

Matching on observables that could influence the dynamics of financial technology adoption enhances the credibility of our identifying assumptions. For instance, several papers show how internet access shapes the digilatization process in banking (e.g., D'Andrea and Limodio 2024; Jiang et al. 2022). We perform the matching using measures of 3G internet coverage, municipality area, population, number of branches, and GDP in 2019. In the Section A2.2 of the Online Appendix, we provide robustness results using the unmatched sample.

In Table 1, we show that municipalities that underwent a branch robbery (treated) and municipalities that were not targeted (control) are similar in terms of GDP per capita, homicide rate, and geographical area. However, treated municipalities are more populous, have a larger GDP, and have more branches than control municipalities.[16] After employing the CEM procedure, these differences disappear, and the control and treatment groups become very similar, even across characteristics that were not included in the matching procedure, such as the share of agriculture, manufacturing, and services in the local GDP.

We analyze how robberies affect municipalities. First, we study how these events affect bank branches by aggregating the stock of cash holdings and deposits of all branches in a given municipality. We then study how the robberies affect the adop-

[16] The disparity in the number of branches is somewhat mechanical as there are no robberies in localities without branches. Despite the correlation between robberies and some municipality characteristics, the events are spread smoothly over the calendar year, that is, there is no apparent seasonality in this activity.

tion of Pix. Our main specification is:

$$y_{mt} = \alpha_m + \alpha_t + \delta_1 PostRob_{mt} + \delta_2 PostRob_{mt} \times BelowMed_m + \beta_t \times 3G\_Cov_m + \epsilon_{mt} \quad (1)$$

where y_{mt} denotes the cash inventory, stock of deposits, or a metric of Pix usage of municipality m in period t. $PostRob_{mt}$ is a dummy variable that takes the value one after municipality m experiences a branch explosion, α_t is a vector of time fixed effects, and α_m is a vector of municipality fixed effects. When y_{mt} is the cash inventory or stock of deposits, time is a calendar month; when it is a measure of Pix usage, a calendar week. To control for heterogeneous trends in Pix adoption related to the quality of the local internet infrastructure, we include the interaction between time fixed effects and internet coverage ($3G\_Cov_m$).[17] We cluster standard errors at the municipality level and weight the regression by CEM weights.

In Figure A2 of the Online Appendix, we show the cumulative distribution of the number of bank establishments across municipalities. 31.1% of municipalities have one bank establishment, and 53.54% have at most two (median). In these places, the consequences of losing an establishment are severely intensified, as there are few or no alternative branches to use. We test this hypothesis by interacting the dummy $PostRob_{mt}$ with the dummy $BelowMed_m$, which takes the value one if municipality m has at most two bank establishments (median).[18] In Section 5.1, we consider alternative cutoffs to classify municipalities with a small number of branches.

Our main coefficient of interest in Equation 1 is δ_2, which gives us the impact of unexpectedly losing a physical branch in municipalities with few alternative branches to access cash (on top of the effect in municipalities with a larger number of branches). We are also interested in δ_1, which represents the effects of bank robberies in munic-

[17]In Section A2.2 of the Online Appendix, we show regressions with and without this control. As we use this variable in the matching procedure, its inclusion does not significantly change the matched sample results. However, in the unmatched sample, this control is relevant, which is in line with research that documents the importance of internet access in shaping the digitalization process (e.g., D'Andrea and Limodio 2024).

[18]In Figure A2 of the Online Appendix, we also show the cumulative distribution function of the number of bank establishments across treated municipalities. The median in this subsample increases to three bank establishments.

ipalities with more alternative branches to access cash. We view the effects in these municipalities as a placebo test since they experience a robbery but cash handling costs rise less in the aftermath of the event.

To investigate the existence of pre-trends and analyze the dynamics of the effects, we also employ a dynamic specification of Equation 1 using leads and lags of the variable $PostRob_{mt}$. As our treatment is staggered and we estimate a two-way fixed effects regression specification, we also provide robustness checks to potential biases in Section A2.5 of the Online Appendix.

After studying the effects of bank robberies on the municipalities' access to cash and Pix adoption, we study how an increase in Pix usage affects the expansion of competitors not targeted by the robbery. We focus on the subsample of municipalities with at most two bank establishments branches, for which we show in Section 3 that the effects on cash handling costs and Pix usage are substantially larger.

We analyze the effects of robberies on the provision of Pix services of institutions that operate in a treated municipality but are not directly affected by the robbery. These are digital institutions and branch-based banks that do not have a branch exploded. Using bank-municipality-month data, we estimate the following specification:

$$\begin{aligned} y_{bmt} = \quad & \alpha_{bm} + \alpha_{bt} + \delta PostRob_{bmt} + \gamma Spillover_{bmt} \times BranchBasedBank_b + \\ & \gamma_d Spillover_{bmt} \times DigitalBank_b + \beta_t \times 3G\_Cov_m + \epsilon_{bmt} \end{aligned} \tag{2}$$

where y_{bmt} is a measure of Pix transactions intermediated by bank b in municipality m in period t. $PostRob_{bmt}$ is a dummy variable that takes the value one after bank b experiences a branch explosion in municipality m, and $Spillover_{bmt}$ takes the value one if bank b does not experience a branch explosion, but another bank in municipality m experienced a branch destruction before time t. The dummy $DigitalBank_b$ takes the value one if bank b is digital, that is, its business model does not rely on physical branches, while $BranchBasedBank_b$ is a dummy variable that takes the value one if the bank has a branch network.

The coefficient δ captures direct effects, while the coefficients γ and γ_d capture spillover effects for branch-based and digital banks, respectively. We include bank-by-time fixed effects (α_{bt}) to control for institution-specific growth trends. These fixed effects play an important role in the estimation of spillovers for digital institutions, as they experienced a higher growth rate during our sample period (Figure A1 of the Online Appendix). We also control for time-invariant bank-municipality heterogeneity by including bank-by-municipality fixed effects (α_{bm}).

Apart from spillovers in payment markets, we also test whether digital institutions are able to expand in credit markets. We estimate Equation 2 using the value of new loans as a dependent variable. If digital institutions provide more payment services, an expansion in credit provision is expected under synergies between payment and credit services. We also assess whether the impact of robbery events in the pre-Pix period is different than that in the post-Pix period. Any heterogeneous response would shed light on the importance of having an inclusive and efficient payment technology to increase the level of competition in the banking industry.

3 Results

3.1 Branch Outcomes: Cash Inventory and Deposits

We start by analyzing how robberies affect the operation of branch-based banks. We aggregate the cash inventory and the stock of deposits of all branches that operate in a municipality. The dataset we use does not contain information on the deposits of digital banks or service stations.[19] We estimate Equation 1 and report results in Table 2. We also report the results of the estimation of a dynamic specification in Figure 2.

As the stock of cash drops to zero in many treated municipalities in the immediate aftermath of the shock, we apply the inverse hyperbolic sine transformation to this variable and use the expression $\exp(\beta) - 1$ to obtain a semi-elasticity (Bellemare and

[19]Municipalities with bank service stations only or without bank establishments are not included in this analysis, as ESTBAN only provides data on bank branches. As a result, in this section, the number of treated municipalities drops from 578 to 455.

Wichman 2020). Robberies have a sizeable effect on the cash stored at branches. In the twelve months after a robbery, the stock of cash at treated municipalities drops by 31.8%. In municipalities with at most two bank establishments, the effect is 94.5%.[20] In contrast, independently of the number of local bank facilities, there is no statistically significant effect on the stock of deposits at the branches located in treated municipalities. In Table A6 of the Online Appendix, we show that these results are robust to different specifications, including one in which we do not use any matching procedure, and in Table A8, we provide robustness checks using Poisson regressions to deal with the high number of zeros post-shock.

In Figure 2, we plot the dynamics of the effects. Treated and control municipalities follow similar trajectories before the robberies. In treated municipalities where the number of branches is below the median (two), the stock of cash drops sharply after the event and starts to grow slowly two months after the shock, suggesting that banks are refurbishing the branches and resuming their cash services after the robberies.[21] However, it remains at a smaller level (in comparison to the counterfactual growth trajectory of control municipalities) even twelve months after the events. In municipalities with more than two branches, the stock of cash also drops in the two months after the event, albeit with a magnitude considerably smaller than that observed in municipalities with at most two branches. However, the effect becomes statistically insignificant after twelve months.

These results provide evidence that the costs of accessing cash increase significantly in places without alternative branches to withdraw and deposit cash. As virtually no branch in our sample closes following these events, the persistence of these results suggests that the explosion event induces the local population to collectively increase the usage of alternative digital payment and demand less cash in the long run.[22]

[20] We need to add the coefficients: $\exp(\delta_1 + \delta_2) - 1 = \exp(-0.383 - 2.509) - 1 = -94.5\%$.

[21] In Figure A3 of the Online Appendix, we plot the time series evolution of the average stock of cash in treated municipalities. In treated municipalities with at most two bank facilities, the stock of cash drops sharply in the month of the event, and then grows slowly, reaching pre-shock levels in twelve months.

[22] If the long-term demand for cash does not shift inwards and banks decide to permanently operate with a smaller cash inventory due to security concerns, their ability to provide payment services would be impaired.

3.2 Impact on Pix

To analyze the repercussions for Pix usage after the bank robberies, we use weekly data and focus on three outcomes: the number of transactions, the value of transactions, and the number of users. We also study usage patterns by the type of users (business or household). Since cash settlement requires both parties to be physically present, it is more likely to be used when the transaction parties are close; when they are distant, cash settlement entails significant transaction costs. As a result, losing a branch and its cash services likely has a larger effect on transactions in which the parties are close. Therefore, we focus on short-distance, intra-municipality Pix transactions in which the payer and payee are in the same municipality.[23]

Table 3 shows estimates for Equation 1. In municipalities with at most two branches (median), there is a sharp increase in Pix usage in the twelve months after the robberies. Compared to control municipalities, the number and value of Pix transactions increase by 24.5% and 15.8%, respectively.[24] In municipalities with more than two branches, there is no effect. This result provides evidence that the fear of going to a bank branch caused by a possible traumatic event does not seem to be the prevailing mechanism behind Pix adoption. The population in localities with more bank branches appears to use other branches to obtain cash, and Pix usage is unaffected.

In Figure 3, we show that treated and control municipalities follow a similar trend before the attacks in terms of Pix usage. However, after the attacks, Pix usage starts to increase disproportionally in treated municipalities with a small number of branches, and this divergence persists even 12 months after the shock. In contrast, treated municipalities whose number of branches is larger (above the median) follow a similar trend as the control group for the whole window.

Table 4 shows that the number of households utilizing Pix for both sending and receiving money increases after the shocks, and Figure 4 shows the dynamics of these effects, which persist for at least twelve months. The number of firms that use Pix to

[23]In Section 4.1, we show effects on credit and debit cards, before and after Pix.

[24]For the number of Pix transactions, $\exp(-0.03+0.249)-1 = 24.5\%$; for the value of Pix transactions, $\exp(-0.015+0.162)-1 = 15.8\%$.

receive payments increases, but there is no effect on the number of firms that use Pix to make payments, consistent with cash not being the predominant payment method in business-to-business transactions before these incidents.

Our results are consistent with several factors posited in the literature that impede financial technology adoption. When the costs of using cash shoot up, Pix emerges as a competitive alternative. However, agents keep using the tool even after the reopening of branches and the subsequent reduction in cash handling costs. This fact is consistent with agents paying the fixed adoption costs (e.g., learning) when the branch is unavailable; when the branch reopens, Pix is more competitive because these costs are sunk. Another explanation is that, as individuals are collectively induced to adopt Pix, its appeal increases permanently due to adoption complementarities.[25]

3.3 Pix Usage Spillovers for Unaffected Institutions

We now turn to whether institutions operating in an affected municipality but not directly affected by the shock experience an increase in Pix usage. These institutions are either digital banks (which, by definition, do not have branches) or branch-based banks that do not have a branch in the municipality or have one that the criminals do not target. While banks' role in cash transactions is indirect and limited to providing convenience by facilitating withdrawals and deposits, in Pix transactions the banks of payers and payees are directly involved. Therefore, spillovers for unaffected institutions are expected if customers of affected banks request the usage of Pix (either to receive or send funds) from clients of other banks. Furthermore, since digital institutions do not operate a network of physical branches and ATMs, their ability to provide payment convenience increases significantly when a locality becomes digital. Therefore, the spillover effects for digital institutions are likely to be more pronounced than those for traditional banks.

We use data for each institution offering Pix payment services and focus on the sample of municipalities with at most two branches. Instead of data at the municipality-

[25] Crouzet et al. (2023) quantify the importance of these alternative explanations.

week level, as in the previous section, we use data at the municipality-bank-week level. This level of granularity allows us to separate the effects on the treated municipalities into effects on the robbed institutions (direct effects) and unaffected institutions (spillover effects). We estimate the spillover effects for two different types of institutions: branch-based banks and digital institutions.

Table 5 shows the results for the estimation of Equation 2. We observe an increase in the number of Pix transactions for both robbed and non-robbed institutions in treated municipalities after the shock. In contrast, when we estimate the impact on the value of Pix transactions, we only observe an increase for non-robbed institutions; for robbed banks, the results are not statistically significant.

For digital institutions, we observe significant spillover effects in Pix usage when an account holder receives a Pix transaction (payee) and when they initiate a Pix transaction (payer). The group of digital institutions is the only one that exhibits significantly positive spillover effects across all measures of Pix usage. Moreover, these institutions are, in general, the ones that experience the largest spillovers.[26] As we include bank-by-time fixed effects, we are comparing the same institution in treated and control municipalities. Therefore, these results are not driven by digital institutions experiencing different aggregate growth rates during our sample period (Figure A1 of the Online Appendix).

The results in this section highlight how Pix adoption spills over to other financial institutions and provide evidence that digital payment methods can spur fintechs' expansion by reducing barriers associated with high cash dependence. We add to previous literature that documents how temporary shocks to cash handling costs affect financial technology adoption (e.g., Crouzet et al. 2023) by documenting changes in the market structure of the payment industry. In the next section, we further add to those results by checking if payment spillovers for fintechs also pave the way for their expansion in credit markets.

[26] In Figure A4 of the Online Appendix, we report results for a dynamic version of Equation 2. We report the coefficients for digital institutions, which display no pre-trend and are in line with those of Table 5.

3.4 Digital Payments, Complementarities and Credit Spillovers

In this section, we study the impacts on new loans to households and firms from affected and unaffected banks. Our results in Table 6 show that the robberies have heterogeneous effects on branch-based banks and digital institutions.[27] While we do not observe any significant change in credit origination of branch-based banks (both robbed and non-robbed) during the twelve months following the robbery events, we find a positive and statistically significant effect for digital banks.

Our sample contains a pre-Pix period, during which we show in Section 4.1 that the usage of credit and debit cards grows after the robberies. We study whether spillovers for digital banks increase when Pix (which has smaller costs and a broader scope than credit and debit cards) becomes available. We find that spillover effects for digital institutions are larger in the post-Pix period. Despite being indicative due to the presence of aggregate time-varying confounders, these results highlight that, besides direct gains for users (for instance, smaller transaction costs and better user experience), digital payment methods may enhance competition in credit markets.[28]

We next provide evidence on the drivers of such results. Payment spillovers for digital banks can lead to credit spillovers in the presence of supply complementarities between credit and payment services. For instance, digital lenders use transaction data to streamline the provision of loans (Ghosh et al. 2023; Gambacorta et al. 2023; Babina et al. 2024). Such information is unavailable for these institutions in a cash-reliant economy, in which traditional banks, by providing cash services, are able to retain more clients and observe cash deposits, withdrawals, and account balances.

We investigate if spillovers for digital institutions are larger for unsecured, information-sensitive loans. In comparison with collateralized, information-insensitive loans, these loans are more likely to benefit from payment information avail-

[27]In Table A11 of the Online Appendix, we estimate the effects of the robberies on aggregate loan origination at the municipality level. Loan amounts do not change significantly after the shock, in contrast to papers that study the effect of (permanent) branch closures on credit (e.g., Bonfim et al. 2021; Nguyen 2019). The temporary nature of the shock and the high level of financial digitalization during our sample period (which is more recent than that of those previous papers) possibly drives these differences.

[28]For example, one possible confounder would arise if digital banks enjoy an enhanced reputation post-Pix.

ability.[29] Table 7 breaks down aggregate results across loan types to households. It shows that digital institutions increase the origination of unsecured loans (credit cards and personal loans) post-robberies; for collateralized loans, the effects are negative but negligible economically. Table 8 provides similar evidence for business loans.

These results are informative for several reasons. First, the fact that affected banks do not change the origination of collateralized loans provides evidence that the reshuffling of credit to digital banks is not driven by an impairment of the lending capacity of these banks. Second, the reshuffling to digital banks only exists when payment information is a key input to the credit origination process. The dynamics of aggregate spillover effects to digital banks (Figure A5 of the Online Appendix) seem to confirm this channel. While the digitalization of payments materializes within three months of the shock (Figure 3), credit expansion to households only begins nine months after the shock, suggesting that the accumulation of payment information data precedes the credit origination process.

Our results shed light on how cashless payments can affect credit market competition by fostering fintech participation. While other sources of complementarities between credit and payments exist, our findings stress the role of supply complementarities arising from the utilization of transaction data in the provision of information-sensitive loans.[30]

4 Other Outcomes

4.1 Other Payment Methods

We extend our analysis to other digital payment methods. Specifically, we investigate the effects of robbery events on the use of credit cards and debit cards. We show re-

[29] Gambacorta et al. (2023) shows that payment transaction data acts as a substitute for collateral in fintech credit in China.

[30] Basten and Juelsrud (2023) attempts to disentangle demand and supply complementarities and find evidence in favor of the former. However, mortgages play a major role in their setting. Our results are consistent with other papers that stress the importance of transaction information for unsecured loans (e.g., Ghosh et al. 2023).

sults on the value of transactions since there is no data on the number of transactions for these methods. To investigate how Pix's emergence changes how people react to decreased access to cash, we divide the analysis into pre- and post-Pix periods.

We present the results in Table A12 of the Online Appendix. Debit cards are substitutes for cash in person-to-merchant transactions. In the pre-Pix period, their usage increases after the robbery events in municipalities whose number of branches is below the median. Debit cards have relatively low costs and are easy to use. Moreover, as they do not entail credit risk, banks do not restrict access or impose tight limits as they do with credit cards. Therefore, even though debit cards have a more limited scope than cash (for example, they cannot be used in person-to-person transactions), they are able to help individuals and firms weather the increase in cash handling costs. Credit cards also grow in the pre-Pix period in municipalities with a number of branches below the median, albeit at a smaller magnitude, possibly reflecting a lack of access and higher costs. In the post-Pix period, these positive effects on credit and debit card usage are reduced.

4.2 Bank Robberies, Other Criminal Activity, and COVID-19

A potential threat to our empirical strategy is the presence of other factors that correlate with bank robberies and affect financial technology adoption. For instance, bank robberies might be correlated to other criminal activities that make individuals hesitant about carrying cash or surges in COVID-19 cases that increase the appeal of digital payments. As we argue in Section 2.3, these robberies are one-off events that non-local criminals perform, and hence they are unlikely to be linked to changes in local criminal activity or the pandemic dynamics.

We provide evidence for this claim by studying the effects on homicides and number of COVID-19 cases. For criminal activity, we focus on homicides because (i) the harmonization across municipalities is more straightforward, and (ii) the issue of underreporting is less severe. First, we note that the homicide rate is not statistically different between our treated and control municipalities even before the matching procedure

(Table 1). Second, in Figure A7 of the Online Appendix, we report results from the estimation of a dynamic version of Equation 1 using homicides and COVID-19 incidence as the dependent variable. We show that robberies are neither preceded nor followed by changes in homicides or COVID-19 cases.

4.3 Adverse Effects: Digital Divide

Results for collateralized loans in Section 3.4 indicate that affected banks keep their lending capacity. However, certain individuals may be adversely affected by the robberies if these banks rely more on digital channels (such as online banking and mobile apps) to weather the short-term shock. This shift might harm individuals who prefer traditional banks (say, because they value in-person interactions and the reputation of these banks) and who are not able to adapt seamlessly to digital customer channels. For instance, Jiang et al. (2022) and Saka et al. (2022) show that younger individuals transition more easily to digital services.

In Table A13 of the Online Appendix, we focus on payroll loans, which are salary- or pension-backed loans in which the debt payments are deducted from salary (or pension) payments. These loans are particularly well-suited for retirees and workers with low unemployment risk (civil servants). We provide evidence that the impact of robberies varies based on consumers' heterogeneous preferences for digital usage and the extent to which individuals encounter barriers to digitalization. Our results show that the incidents reduce payroll operations in targeted branches and that spillovers to unaffected banks do not offset this loss. However, these significant reductions are concentrated among retirees (older borrowers) rather than among active workers (younger borrowers). These results corroborate previous findings highlighting the distributional effects of digitization when access to or preferences for digital technologies are heterogeneous.

4.4 Real Effects

The temporary impairment of branches' cash services might represent a negative shock to the local economy, despite the generation of positive side effects on digitalization. In this section, we analyze the effects on hirings and firings of formal firms located in treated municipalities. Table A14 of the Online Appendix shows that, at least according to these measures, the shocks do not seem to affect the local real economy. However, these results should be interpreted cautiously because hiring and firing decisions involve costs and reflect medium- and long-term expectations. Moreover, this data only reflects formal firms' decisions, and the country has a large incidence of informality.

5 Robustness Checks

5.1 Heterogeneity by the Number of Bank Establishments: Alternative Cutoffs

In Section 3, we show that the effects on cash supply services and Pix usage vary by the number of branches in the municipality. We use the cutoff of two branches to split municipalities into above-median and below-median, where two is the median of the distribution of bank establishments across municipalities (Figure A2a of the Online Appendix). In this section, we modify Equation 1 to consider alternative cutoffs:

$$\begin{aligned} y_{mt} = \quad & \alpha_m + \alpha_t + \delta_{1,c} PostRob_{mt} \times (Branches > c)_m + \\ \delta_{2,c} \quad & PostRob_{mt} \times (Branches \leq c)_m + \beta_t \times 3G\_Cov_m + \epsilon_{mt} \end{aligned} \tag{3}$$

where $(Branches > c)_m$ is a dummy variable that takes the value one if the number of branches of municipality m is larger than the cutoff c, and $(Branches \leq c)_m$ is a dummy variable that takes the value one if the number of branches of municipality m is smaller or equal than the cutoff c. We run a separate regression for each value of $c \in \{2, 3, 4, 5, 6, 7, 8, 9, 10\}$. We are interested in how the coefficient $\delta_{2,c}$ changes when the cutoff c increases, that is, when the number of alternative branches in the treated municipality gets larger.

In Figure A6 of the Online Appendix, we see that, for both the effects on cash inventory and Pix usage, the coefficient $\delta_{2,c}$ tends to decrease (in absolute value) when we increase the cutoff. This corroborates the hypothesis that the number of branches moderates the results. Moreover, it shows that the cutoff choice of Section 3 is innocuous since results are still valid under alternative cutoffs.[31]

5.2 Stacked Difference-in-differences

Recent articles have shown that when treatment is staggered, two-way fixed effects models can lead to biased results.[32] We implement a stacked regression estimation to deal with this issue (Baker et al. 2022). We augment the stacked difference-in-differences approach using the CEM procedure as in our baseline specifications.

We show the results in Table A10 of the Online Appendix. The results are quantitatively similar to those in our baseline specification (Table 3). These results corroborate our findings using the baseline specification that municipalities experience an increase in Pix usage after the robberies and that the number of alternative branches in the same municipality moderates these results.

6 Conclusion

We show that physical branches and financial technology adoption have considerable linkages. We demonstrate that the sudden interruption of branches' cash services increases cash handling costs and leads to a persistent rise in the usage of digital payment technologies.

[31]Panel (a) of Figure A6 shows that the number of treated municipalities with branches below the cutoff increases sharply for smaller cutoff values; for larger values of the cutoff, the number of treated municipalities with branches below the cutoff increases less. This is in line with most treated municipalities having few branches (Figure A2b). As a result, the coefficient $\delta_{2,c}$ tends to change less for larger values of the cutoff.

[32]Baker et al. (2022) and Roth et al. (2023) provide surveys of this literature.

We show that the digitalization of payments generates local spillover effects for digital institutions not directly affected by the robberies. These institutions do not offer cash services, which require expensive investments in a physical network of branches and ATMs. When a locality reduces its reliance on cash, these institutions become more attractive as payment providers and increase the provision of digital payment services. Moreover, since transaction data is a key input in the provision of information-sensitive loans, the increase in digital payments enables their growth in unsecured credit products. The results shed some light on the role of new digital payment methods in increasing financial competition by boosting digital institutions' ability to compete with conventional banks in both payment and credit markets.

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Tables

Table 1: Original and Matched Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Original sample			Matched sample		
	Treated	Control	Diff.	Treated	Control	Diff.
Panel A: CEM variables						
3G access	79.8	77.5	2.3***	79.7	79.7	-0.0
(% of the population, 2019)	(18)	(18.3)	(0.8)	(17.9)	(18)	(0.8)
Municial area	1324.8	1097.8	227.0	1081.1	995.8	85.2
(in km2)	(4227.4)	(3304.5)	(183.0)	(1911.6)	(2070)	(98.9)
Population	51.3	25.9	25.4***	41.9	34.6	7.3*
(thousands, 2019)	(144.4)	(60.2)	(6.1)	(75.7)	(71)	(4.1)
GDP	1712.6	793.9	918.7***	1357	1225.2	131.8
(in 1,000,000 BRL)	(5642.9)	(2839.2)	(238.7)	(3375.9)	(3386)	(214.3)
Bank facilities	8.7	4.5	4.2***	6.8	6.0	0.7
(2019)	(31.7)	(10.9)	(1.3)	(13.9)	(13.5)	(0.8)
Panel B: Variables not included in the CEM procedure						
Share agriculture	16.3	18.6	-2.2***	16.5	17.4	-0.9
(% of value added, 2019)	(14.8)	(15)	(0.7)	(14.8)	(14.8)	(0.7)
Share manufacturing	15.6	13.6	1.9***	15.4	14.5	0.9
(% of value added, 2019)	(14.8)	(13.9)	(0.7)	(14.7)	(14.1)	(0.7)
Share services	37.3	35.6	1.7***	37.2	37.0	0.2
(% of value added, 2019)	(13.6)	(13.1)	(0.6)	(13.4)	(13.7)	(0.6)
GDP per capita	26.6	25.5	1.1	26.5	27.8	-1.3
(in 1,000 BRL 2019)	(28)	(26.2)	(1.2)	(28)	(33.7)	(2.0)
Homicide rate	14.8	14.6	0.2	14.8	14.5	0.3
(in 2019)	(35.3)	(42.4)	(1.9)	(35.4)	(41.1)	(1.9)
Number of observations	578	4164		569	4089	

Notes: Panel A compares baseline characteristics of the variables used in the Coarsened Exact Matching (CEM) procedure; Panel B compares the baseline characteristics of variables not used in the CEM procedure. In columns 1-3, we use the original sample; in columns 4-6, we use the matched sample. In columns 1-2 (4-5), we report unweighted (weighted by CEM weights) means and standard deviations. In columns 3 and 6, we report the $\hat{\beta}$ of the regression $y_m = \alpha + \beta Treated_m + \epsilon_m$, where $Treated_m$ is a binary variable that takes the value 1 if municipality m experiences a robbery that results in the destruction of a bank establishment. In column 3, we run an OLS regression, while in column 6 we run a WLS regression using the CEM weights.

Table 2: Bank Robberies, Access to Cash and Deposits in Branch-Based Banks

	(1)	(2)	(3)	(4)
	Cash inventory		Deposits	
Post Robbery	-1.014***	-0.383***	-0.003	-0.008
	(0.140)	(0.088)	(0.006)	(0.005)
Post Robbery×(Branches≤Median)		-2.509***		0.022
		(0.456)		(0.020)
Municipality FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
3G Internet Cov.×Month FE	Yes	Yes	Yes	Yes
Observations	165,810	165,810	165,686	165,686
Municipalities	2,966	2,966	2,966	2,966
Treated municipalities	446	446	446	446
R^2	0.815	0.818	0.987	0.987

Notes: The table presents estimates of Equation 1. In all regressions, the post-robbery window has a length of 12 months and the pre-robbery window has a length of 6 months. We consider all robberies that caused the destruction of branches between 2018 and 2021 and all municipalities that have an active branch, that is, municipalities that only have a service station (or no bank establishment) are not included due to lack of data. In columns 1 and 2, the dependent variable is the inverse hyperbolic sine transformation of the cash inventory of all branches in a given municipality; in columns 3 and 4, the natural logarithmic of the stock of deposits of all branches in a given municipality. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Branches≤Median is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

Table 3: Bank Robberies and Intra-Municipality Pix Usage

	(1)	(2)	(3)	(4)
	Quantity		Value	
Post Robbery	0.083***	-0.030	0.058**	-0.015
	(0.030)	(0.031)	(0.027)	(0.026)
Post Robbery×(Branches≤Median)		0.249***		0.162***
		(0.050)		(0.050)
Municipality FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Week×3G Coverage FE	Yes	Yes	Yes	Yes
Observations	448,028	448,028	448,028	448,028
Municipalities	4,129	4,129	4,129	4,129
Treated municipalities	47	47	47	47
R^2	0.992	0.992	0.972	0.972

Notes: The table presents estimates of Equation 1. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. In columns 1-2 (3-4), the dependent variable is the inverse hyperbolic sine transformation of the total number (value) of intra-municipality Pix transactions in the municipality. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Branches≤Median is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

Table 4: Bank Robberies and the Number of Pix Users in Intra-Municipality Transfers

	(1)	(2)	(3)	(4)
	Household		Firms	
	Payer	Payer	Payer	Payee
Post Robbery	-0.026	-0.029	0.031	0.033
	(0.030)	(0.029)	(0.040)	(0.046)
Post Robbery $\times$ (Branches $\leq$ Median)	0.244***	0.247***	0.087	0.224***
	(0.049)	(0.049)	(0.072)	(0.064)
Municipality FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Week $\times$ 3G Coverage FE	Yes	Yes	Yes	Yes
Observations	448,028	448,028	448,028	448,028
Municipalities	4,129	4,129	4,129	4,129
Treated municipalities	47	47	47	47
R^2	0.993	0.993	0.985	0.984

Notes: The table presents estimates of Equation 1. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. In column 1 (3), the dependent variable is the inverse hyperbolic sine transformation of the total number of households (firms) that are payers in Pix intra-municipality transactions. In column 2 (4), the dependent variable is the inverse hyperbolic sine transformation of the number of households (firms) that are payees in intra-municipality Pix transactions. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Branches$\leq$Median is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

Table 5: Bank Robberies and Pix Usage Spillovers

	(1)	(2)	(3)	(4)
	Household		Firms	
	Payer	Payee	Payer	Payee
Panel A: Number of Pix Transactions				
Post Robbery (Direct Effects)	0.262***	0.184***	0.314***	0.498***
	(0.062)	(0.040)	(0.098)	(0.083)
Spillover Effects×Branch-based	0.067***	0.090***	0.057	0.110
	(0.020)	(0.019)	(0.041)	(0.068)
Spillover Effects×Digital	0.178***	0.161***	0.062*	0.092**
	(0.022)	(0.023)	(0.036)	(0.047)
Observations	19,070,196	19,070,196	8,260,940	8,260,940
R^2	0.922	0.925	0.832	0.837
Panel B: Value of Pix Transactions				
Post Robbery (Direct Effects)	-0.030	-0.084	-0.033	0.148
	(0.095)	(0.067)	(0.179)	(0.172)
Spillover Effects×Branch-based	0.124**	0.171***	0.359**	0.347*
	(0.056)	(0.050)	(0.160)	(0.193)
Spillover Effects×Digital	0.238***	0.160***	0.245*	0.357***
	(0.058)	(0.059)	(0.126)	(0.125)
Observations	19,070,196	19,070,196	8,260,940	8,260,940
R^2	0.820	0.825	0.724	0.742
Muni x Institution FE	Yes	Yes	Yes	Yes
Week x 3G Coverage FE	Yes	Yes	Yes	Yes
Week x Institution FE	Yes	Yes	Yes	Yes
# Municipalities	3,967	3,967	3,967	3,967
# Affected Municipalities	22	22	22	22

Notes: The table presents estimates of Equation 2. The sample is restricted to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. We report coefficients of the interaction of the post-robbery dummy with dummies for institution types. In Panel A (B), the dependent variable is the inverse hyperbolic sine transformation of the total number (value) of intra-municipality Pix transactions In column 1 (3), we consider Pix intra-municipality transactions in which households (firms) are payers. In column 2 (4), we consider Pix intra-municipality transactions in which households (firms) are payees. Standard errors are clustered at the municipality-bank level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. As the matching is at the municipality level but the data is at the municipality-institution level, regressions are weighted by the CEM weights times the inverse of the number of institutions in a given municipality-week pair.

Table 6: Bank Robberies, Pix and Credit Reallocation

	(1)	(2)	(3)	(4)
	Households Credit Vol.		Firms Credit Vol.	
Post Robbery (Direct Effects)	-0.087	-0.095	0.205	0.271
	(0.066)	(0.075)	(0.145)	(0.158)
Post Robbery (Direct Effects)×Post Pix		0.065		-0.494*
		(0.077)		(0.289)
Spillover Effects×Branch-based	0.0230	0.0220	0.090	0.081
	(0.019)	(0.020)	(0.071)	(0.078)
Spillover Effects×Branch-based×Post Pix		0.011		0.060
		(0.047)		(0.181)
Spillover Effects×Digital	0.120***	0.074*	0.274***	-0.059
	(0.037)	(0.040)	(0.0139)	(0.078)
Spillover Effects×Digital×Post Pix		0.136*		0.834***
		(0.076)		(0.333)
Institution×Municipality FE	Yes	Yes	Yes	Yes
Month×3G Coverage FE	Yes	Yes	Yes	Yes
Month×Institution FE	Yes	Yes	Yes	Yes
Observations	25,304,371	25,304,371	7,005,771	7,005,771
Municipalities	4,180	4,180	4,180	4,180
Affected Municipalities	235	235	235	235
R^2	0.823	0.823	0.745	0.745

Notes: The table presents estimates of Equation 2 augmented with interactions with dummies that take the value one after the Pix launch. The sample is restricted to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. We report coefficients of the interaction of the post-robbery dummy with dummies for institution types and the post-Pix period. In columns 1-2 (3-4), the dependent variable is the inverse hyperbolic sine transformation of the value of new loans to households (firms). Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5.

Table 7: Bank Robberies and Household Loan Types

	(1)	(2)	(3)	(4)	(5)	(6)
	Credit Card		Personal Loan		Collateralized Loans	
Post Robbery (Direct Effects)	-0.007	-0.015	-0.099***	-0.111***	0.030	0.081
	(0.052)	(0.057)	(0.035)	(0.035)	(0.216)	(0.228)
Post Robbery (Direct Effects)×Post Pix		0.060		0.091		-0.386
		(0.108)		(0.130)		(0.657)
Spillover Effects×Branch-based	0.013	0.012	-0.008	-0.010	0.012	0.010
	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)
Spillover Effects×Branch-based×Post Pix		0.006		0.015		0.008
		(0.028)		(0.036)		(0.034)
Spillover Effects×Digital	0.103***	0.054	0.085**	0.099**	-0.002***	-0.001***
	(0.037)	(0.042)	(0.038)	(0.050)	(0.000)	(0.000)
Spillover Effects×Digital×Post Pix		0.147**		-0.041		-0.002
		(0.073)		(0.066)		(0.001)
Muni×Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
Month×3G Coverage FE	Yes	Yes	Yes	Yes	Yes	Yes
Month×Institution FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.893	0.893	0.745	0.745	0.638	0.638
# Observations	25,344,364	25,344,364	25,344,364	25,344,364	25,344,364	25,344,364

Notes: The table presents estimates of Equation 2 augmented with interactions with dummies that take the value one after the Pix launch. The sample is restricted to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. We report coefficients of the interaction of the post-robbery dummy with dummies for institution types and the post-Pix period. In all columns, the dependent variable is the inverse hyperbolic sine transformation of the value of new loans. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5.

Table 8: Bank Robberies and Business Loan Types

	(1)	(2)	(3)	(4)
	Total minus Credit Card		Credit Card	
Post Robbery (Direct Effects)	0.172	0.245	0.099	0.127*
	(0.154)	(0.165)	(0.072)	(0.068)
Post Robbery (Direct Effects)×Post Pix		-0.549		-0.210
		(0.367)		(0.279)
Spillover Effects×Branch-based	0.136*	0.139*	-0.008	-0.030
	(0.070)	(0.077)	(0.034)	(0.037)
Spillover Effects×Branch-based×Post Pix		-0.023		0.143*
		(0.180)		(0.076)
Spillover Effects×Digital	-0.003	-0.017	0.241*	-0.075*
	(0.069)	(0.078)	(0.132)	(0.045)
Spillover Effects×Digital×Post Pix		0.037		0.789**
		(0.163)		(0.313)
Muni×Institution FE	Yes	Yes	Yes	Yes
Month×3G Coverage FE	Yes	Yes	Yes	Yes
Month×Institution FE	Yes	Yes	Yes	Yes
R^2	0.744	0.744	0.740	0.740
# Observations	7,010,346	7,010,346	7,010,346	7,010,346

Notes: The table presents estimates of Equation 2 augmented with interactions with dummies that take the value one after the Pix launch. The sample is restricted to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. We report coefficients of the interaction of the post-robbery dummy with dummies for institution types and the post-Pix period. In all columns, the dependent variable is the inverse hyperbolic sine transformation of the value of new loans. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5.

Figures

Figure 1: Examples of Branches Destroyed after Robberies

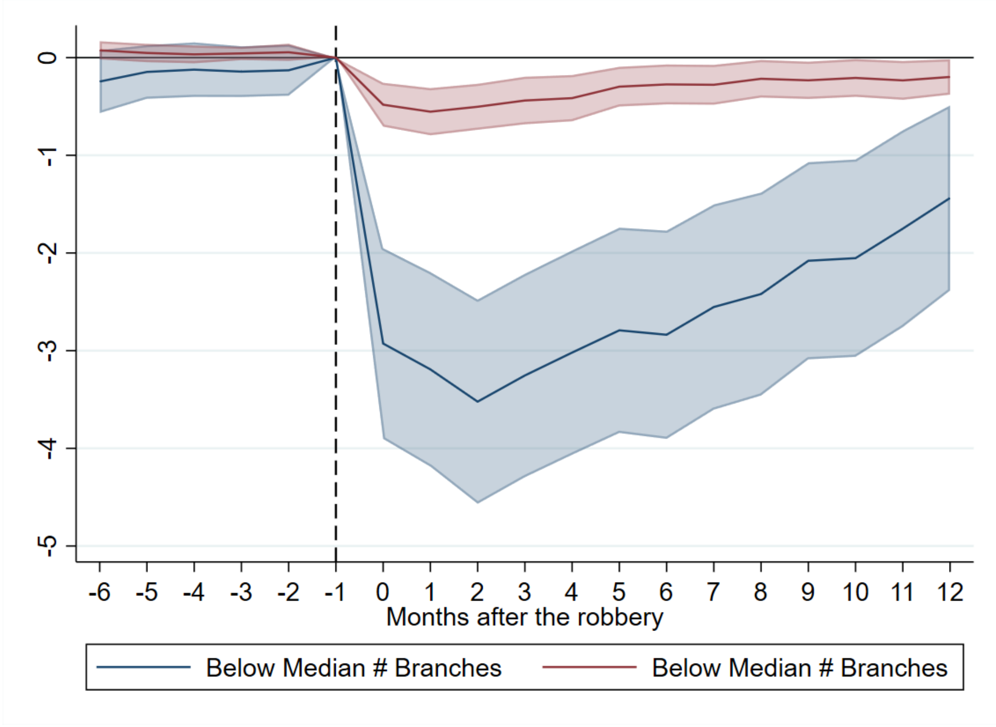
Source: https://atarde.com.br/bahia/ataques-a-bancos-na-bahia-aumentam-mais-de-400-no-periodo-de-janeiro-a-abril-1153220.
Picture by: Olga Leiria / Ag. A TARDE

(**a**) A Banco do Brasil branch destroyed during an attack in the state of Bahia in April 2021

Source: https://g1.globo.com/mg/sul-de-minas/noticia/seis-agencias-bancarias-sao-alvos-de-explosao-e-roubo-em-tres-cidades-de-mg.ghtml. Picture by: Diego Batista/ Areado Notícias

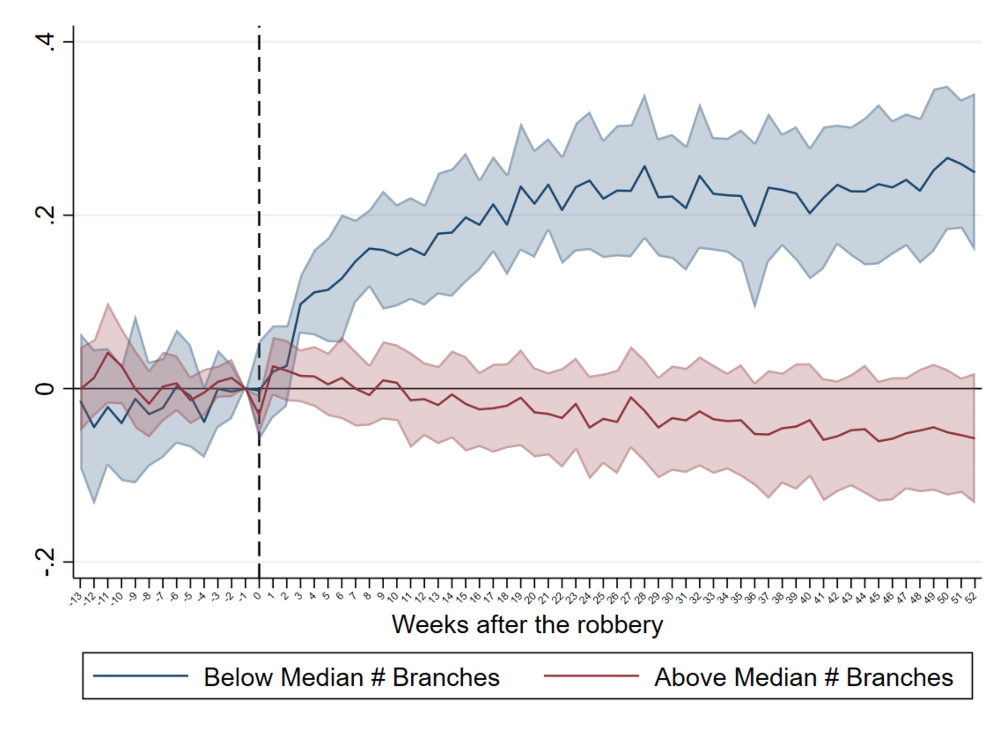
(**b**) A Banco Bradesco branch destroyed during an attack in the state of Minas Gerais in April 2018

Figure 2: Bank Robbery and Access to Cash in Branch-Based Banks

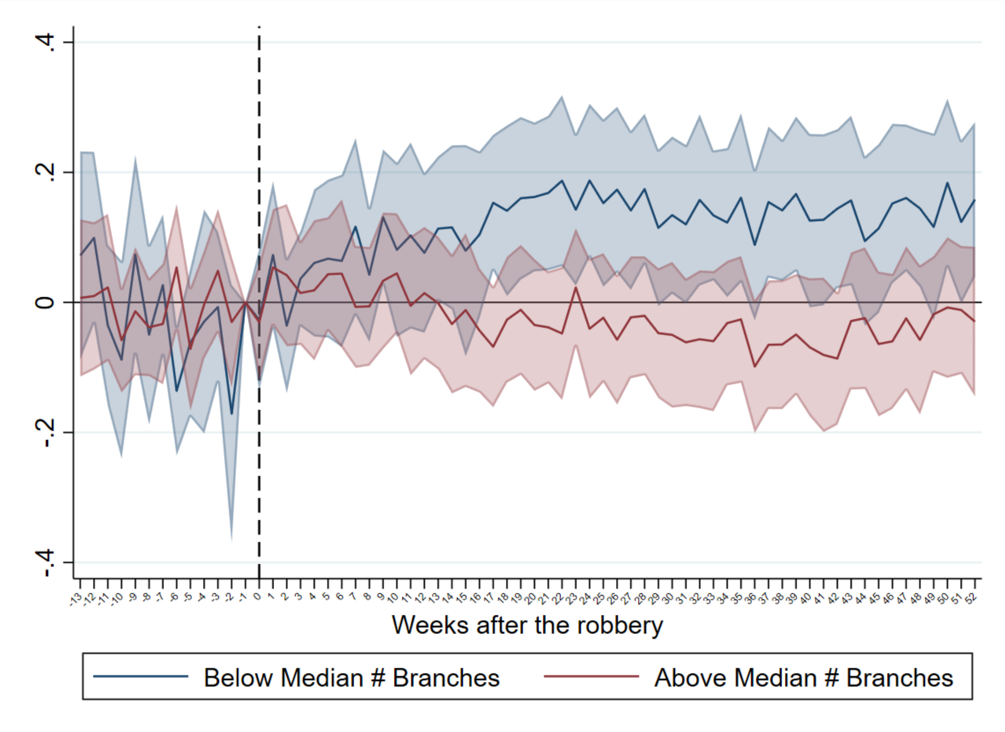


Notes: The figures report results from a dynamic version of Equation 1. We consider all robberies that caused the destruction of branches between 2018 and 2021 and all municipalities that have an active branch, that is, municipalities that only have a service station (or no bank establishment) are not included due to lack of data. We report 95% confidence intervals based on standard errors clustered at the municipality level. All specifications include municipality and month fixed effects and time-varying heterogeneous effects of municipal 3G internet population coverage. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Below Median # Branches refers to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. Above Median # Branches refers to municipalities with more than two branches.

Figure 3: Bank Robberies and Pix Adoption



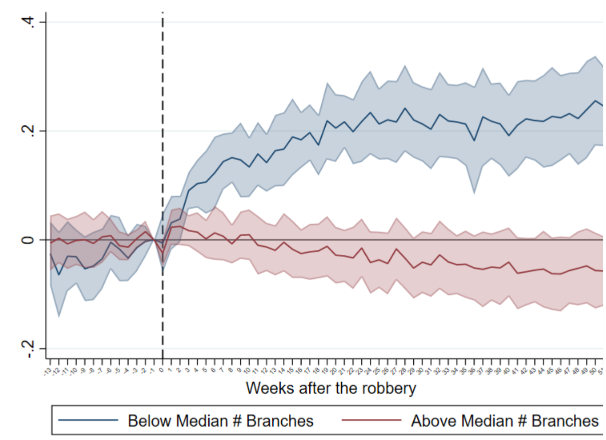
(**a**) Number of Pix Transactions



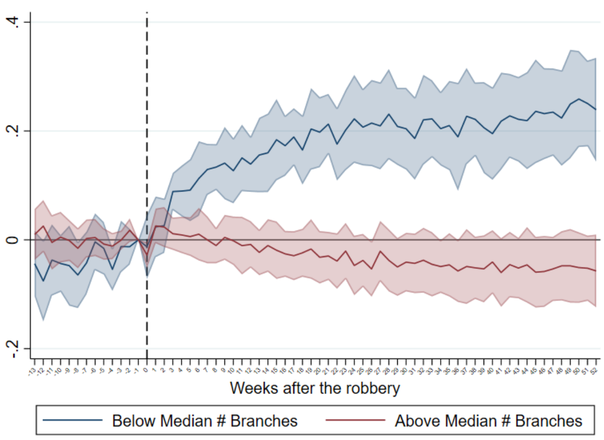
(**b**) Value of Pix Transactions

Notes: The figures report results from the estimation of a dynamic version Equation 1. We report 95% confidence intervals based on standard errors clustered at the municipality level. All specifications include municipality and week fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. We use the inverse hyperbolic sine transformation of the original dependent variable. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Below Median # Branches refers to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. Above Median # Branches refers to municipalities with more than two branches.

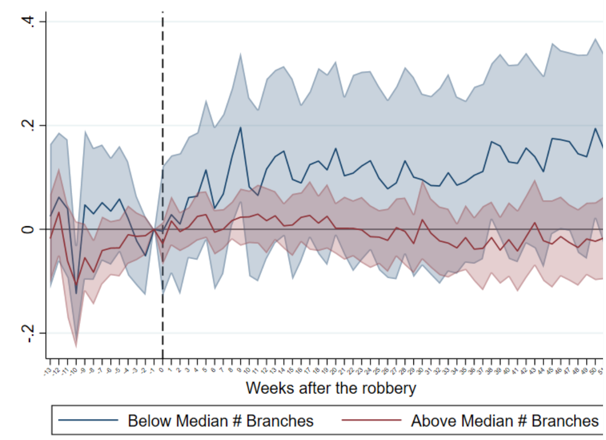
Figure 4: Bank Robberies and Pix Users by Transaction Type



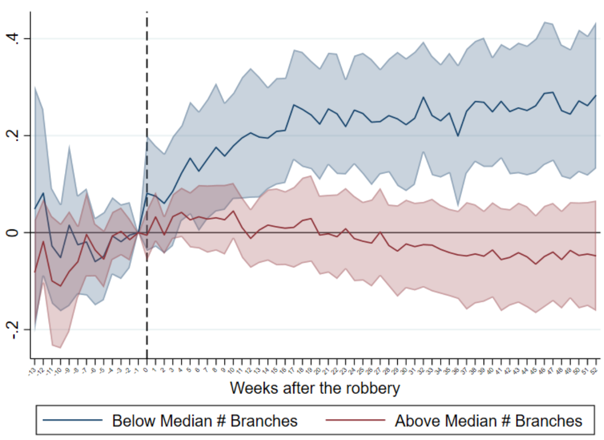
(a) Average Pix Non-Business Users - Payer



(b) Average Pix Non-Business Users - Payee



(c) Average Pix Business Users - Payer



(d) Average Pix Business Users - Payee

Notes: The figures report results from the estimation of a dynamic version Equation 1. We report 95% confidence intervals based on standard errors clustered at the municipality level. All specifications include municipality and week fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. We use the inverse hyperbolic sine transformation of the original dependent variable. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Below Median # Branches refers to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. Above Median # Branches refers to municipalities with more than two branches.

Online Appendix

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A1 Institutional setting: additional details

A1.1 Transactions per customer channel in 2020

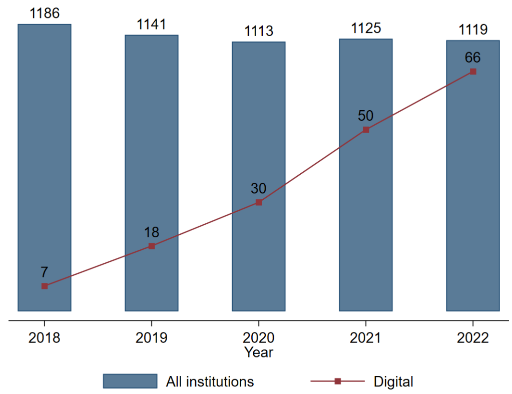
Table A1: Transactions per Customer Channel in 2020

	Branch and service station	ATM	Phone	Internet / Mobile	Bank agent
Panel A: Participation (%) of each channel (including all transaction types)					
Share	9.3	23.8	2.0	53.7	11.2
Panel B: Share (%) of each transaction type for a given channel					
Boleto payment	22.3	5.6	0.3	8.6	60.1
Statement / balance check	14.4	35.8	73.9	37.0	7.4
Deposit	10.7	10.4	0.0	0.0	12.4
Loans	8.9	0.6	0.4	0.8	1.4
Other	25.0	7.0	25.0	47.8	3.1
Cash withdrawal	7.2	38.7	0.0	0.0	15.5
Credit transfer	11.4	1.9	0.4	5.8	0.0
Pix	0.0	0.0	0.0	0.0	0.0
Panel C: Share (%) of each channel for a given transaction type					
Boleto payment	13.9	9.1	0.0	31.3	45.7
Statement / balance check	4.2	26.5	4.7	62.0	2.6
Deposit	20.5	50.8	0.0	0.0	28.7
Loans	51.6	9.5	0.5	28.3	10.1
Other	7.6	5.4	1.7	84.2	1.1
Cash withdrawal	5.8	79.3	0.0	0.0	15.0
Credit transfer	22.9	9.6	0.2	67.3	0.1
Pix	0.9	0.0	0.0	99.1	0.0

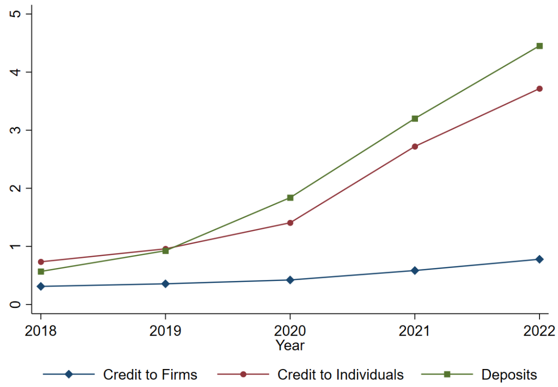
Notes: In Panel A, we show the participation of each channel considering all transaction types (row add up to 100). In Panel B, we compute the share of each transaction type in a given channel (columns add up to 100). In Panel C, we compute the share of each channel for a given transaction type (rows add up to 100). Bank agents refer to non-financial establishments, usually retailers, that provide financial services on behalf of a bank.

A1.2 Participation of digital banks

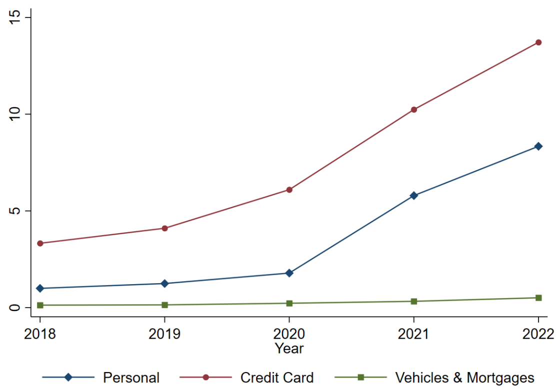
Figure A1: Quantity and Market Shares (%) of Digital Institutions



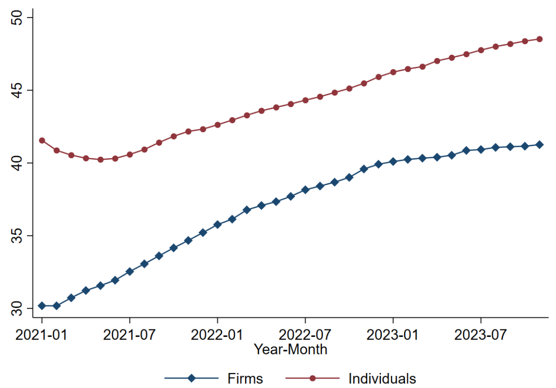
(a) Total number of financial institutions and number of digital institutions



(b) Market share (%) of digital institutions: deposits and credit to firm and individuals



(c) Market share (%) of digital institutions: different types of loans to individuals



(d) Market share (%) of digital institutions: number of registered Pix keys

Notes: Panel A reports the total number of active financial institutions and the number of digital institutions. Digital banks are financial institutions that rely exclusively on digital customer channels. We plot the participation of digital banks in the stock of deposits and loans to firms and individuals (Panel B) and the stock of three loan types to individuals: personal loans, credit cards, and vehicles & mortgages (Panel C). In Panel D, we plot the share of Pix keys (aliases) of firms and individuals associated with accounts in digital banks.

A1.3 Pix transactions by participant types

Table A2: Pix Transactions by Participant Types in 2021

	Quantity		Value	
	In billion	Share (%)	In BRL million	Share (%)
No info (intrabank)	1.57	16.4	700	13.4
Involves government	0.01	0.1	12	0.2
B2B	0.21	2.2	1594	30.5
B2P	0.68	7.1	565	10.8
P2B	1.14	11.9	454	8.7
P2P	5.94	62.3	1897	36.3
Total	9.55		5221	

Notes: B2B: business-to-business; B2P: business-to-person; P2B: person-to-business; P2P: person-to-person; involves government: a government agency is the payer or the payee. It is not possible to categorize transactions between accounts of the same institution.

A1.4 Payment methods

Table A3: Composition (%) of the Main Means to Transfer Resources in Brazil

	2019		2020		2021	
	Quantity	Value	Quantity	Value	Quantity	Value
TED	2.4	41.3	3.9	45.1	2.0	45.5
Intrabank transfer	3.1	23.2	3.1	22.6	1.7	19.6
Direct debit	13.2	7.8	13.0	6.7	10.5	6.1
Boleto	17.8	15.8	18.4	15.5	14.0	14.2
Credit card	22.0	1.9	20.6	1.8	20.1	2.0
Debit card	24.8	1.2	24.3	1.3	21.2	1.2
Prepaid card	4.6	0.1	6.3	0.1	9.1	0.2
Cash withdrawal	10.5	5.8	8.7	4.6	5.7	3.1
Other (checks, ...)	1.7	3.0	1.4	2.0	0.7	1.5
Pix	0.0	0.0	0.4	0.2	15.0	6.7

Notes: Intrabank transfer refers to wire transfers involving accounts in the same bank. TED (*transferência eletrônica disponível*) was the main credit transfer option before Pix. *Boleto* refers to invoices that can be paid electronically or physically (at an ATM, branch, or stores that provide services on behalf of banks). As cash transactions are not recorded, we provide data on cash withdrawals. Direct debit refers to the automatic payment of recurrent (mostly utility) bills. Pix was launched in November 2020. Source: Brazilian Central Bank.

A1.5 Pix usage and municipality characteristics

Table A4: Municipality Characteristics and Pix Usage

	Terciles: number of Pix transactions per inhabitant			Terciles: value of Pix transactions per inhabitant		
	1 (low)	2	3 (high)	1 (low)	2	3 (high)
Panel A: Socio-economic characteristics						
GDP	162	286	3533	154	313	3515
(BRL millions, 2019)	(180)	(360)	(21828)	(170)	(514)	(21828)
GDP per capita	17.2	22.1	34.3	12.5	23.1	38.0
(BRL thousands, 2019)	(15.7)	(21.7)	(33.0)	(9.9)	(23.0)	(31.6)
Share agriculture	22	20	13	18	22	15
(% of value added, 2019)	(15)	(15)	(14)	(14)	(16)	(15)
Share manufacturing	8	12	19	7	12	21
(% of value added, 2019)	(10)	(13)	(16)	(8)	(13)	(15)
Share services	27	34	44	26	34	44
(% of value added, 2019)	(9)	(11)	(15)	(8)	(11)	(14)
Population	12	15	86	14	16	83
(thousands, 2019)	(12)	(15)	(379)	(14)	(25)	(379)
3G/4G access	65	77	88	66	77	87
(% of population, 2020)	(19)	(16)	(13)	(19)	(17)	(14)
Panel B: Financial sector characteristics						
Branches' cash inventory	1.6	2.7	30.7	2.0	3.0	29.3
(BRL millions, 2019)	(1.8)	(2.8)	(352.8)	(2.2)	(3.6)	(346.9)
Total deposits	37	77	1464	39	77	1415
(BRL millions, 2019)	(76)	(93)	(18046)	(79)	(97)	(17741)
Deposits HHI	0.82	0.67	0.45	0.80	0.68	0.46
(2019, conditional on having a branch)	(0.25)	(0.29)	(0.26)	(0.26)	(0.29)	(0.27)
Number of branches	0.6	1.3	8.9	0.6	1.3	8.8
(2019)	(1.0)	(1.5)	(59.9)	(1.0)	(1.6)	(59.9)
Number of observations	1856	1856	1856	1856	1856	1856

Note: We group municipalities by measures of Pix usage accumulated between November 2020 and August 2021. The variables branches' cash inventory, deposits HHI, and total deposits are computed conditional on the municipality having a branch. We report means and, in parentheses, standard errors.

A1.6 Multiple- and single-robbery municipalities

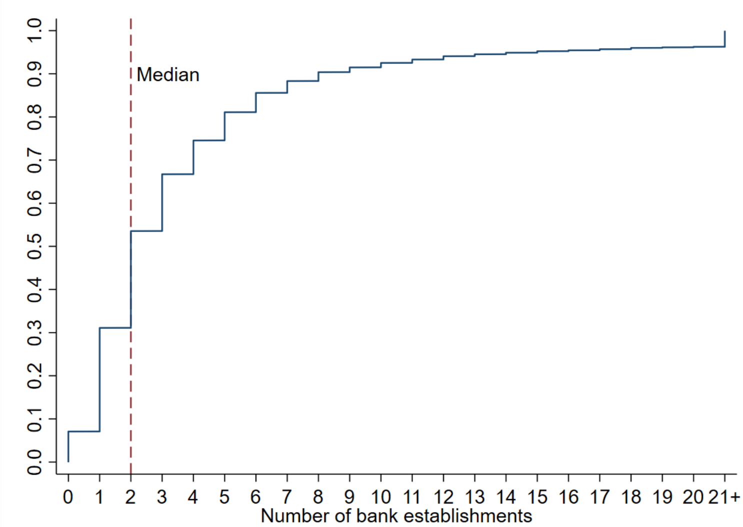
Table A5: Municipality Characteristics and Pix Usage

	Multiple time	
	No	Yes
Branches	4.6	48.6
Service stations	4.1	28.7
Population (in 1,000)	51.3	381.6
GDP (in 1,000,000 BRL)	1713	17932
GDP per capita (in 1,000 BRL)	26.6	32.5
3G Population covered	79.8	87.0
Area (in km2)	1325	2950
Municipalities	578	136

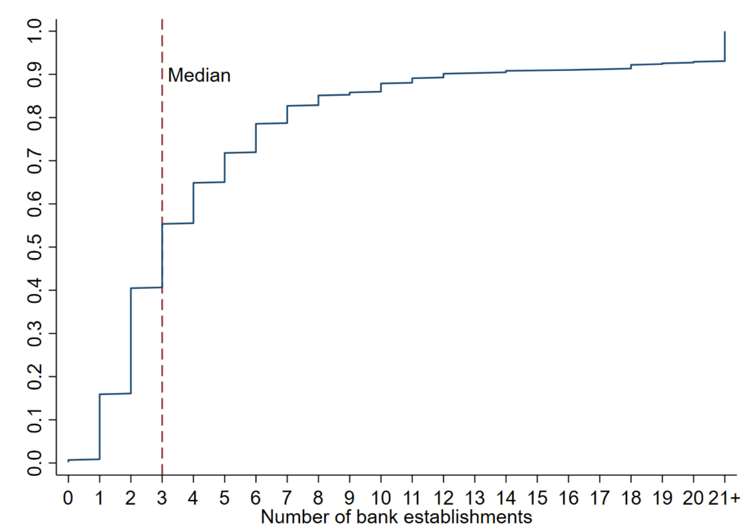
Note: We group municipalities by whether they were affected by different raids during our sample period, that is, if they were robbed in at least two different months. All municipal characteristics are measured in 2019.

A1.7 Distribution of the number of branches and service stations across municipalities

Figure A2: Bank Establishments per Municipality: Cumulative Distribution Function



(**a**) All municipalities

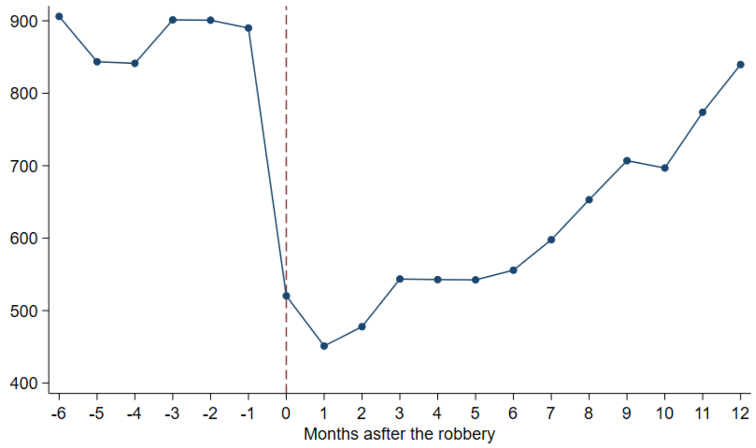


(**b**) Treated municipalities

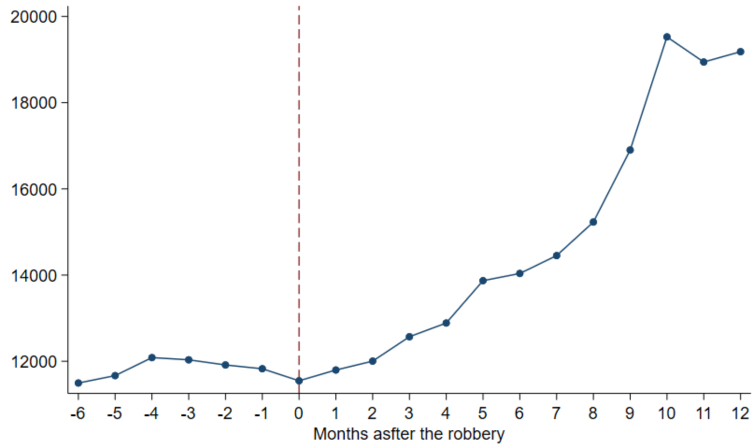
Notes: The figure reports the cumulative distribution function (cdf) of the number of branches and bank service stations per municipality in December 2019. In Figure (a), use consider all municipalities. In Figure (b), we use the treated municipalities after applying the filters described in Section 2.4.

A1.8 The evolution of aggregate cash inventory in treated municipalities

Figure A3: Evolution of Average Aggregate Cash Holdings (in 1,000 BRL) in Treated Municipalities



(**a**) Treated municipalities with at most two bank facilities



(**b**) Treated municipalities with at least three bank facilities

Notes: The figure reports the average aggregate cash holdings (in thousands BRL) of branches in treated municipalities before and after the robberies. In Figure (a), we plot averages for treated municipalities with at most two bank facilities in December 2019; in Figure (b), averages for treated municipalities with at least three bank facilities in December 2019.

A1.9 Main sources of information

Branch network and service stations in Brazil: Central Bank of Brazil, *Divulgações Mensais - Evolução do SFN*, access: https://www.bcb.gov.br/estabilidadefinanceira/evolucaosfnmes, 2021, December, *Quadro 04 - Atendimento bancário no País - Distribuição do Quantitativo de Municípios por Região e UF*, *Quadro 7 - Quantitativo de municípios com atendimento bancário no País*. The Central Bank divides the municipality of Brasília into 21 districts. We adjust the data and consider Brasília as one municipality (instead of 21). Moreover, monthly information on branches can be obtained at https://www.bcb.gov.br/fis/info/agencias.asp?frame=1. To obtain the number of branches from this source, we selected the categories (*segmento*): *Banco Comercial, Banco Comercial Estrangeiro - Filial no país, Banco do Brasil - Banco Múltiplo, Banco Múltiplo, Banco Múltiplo Cooperativo, Caixa Econômica Federal*.

Branch network in the US: FDIC, Quarterly Banking Profile, Fourth Quarter 2021, Table 9. Access: https://www.fdic.gov/analysis/quarterly-banking-profile/fdic-quarterly/2022-vol16-1/fdic-v16n1-4q2021.pdf.

Banks' balance sheet information in Brazil: IF.data, Central Bank of Brazil, access: https://www3.bcb.gov.br/ifdata/.

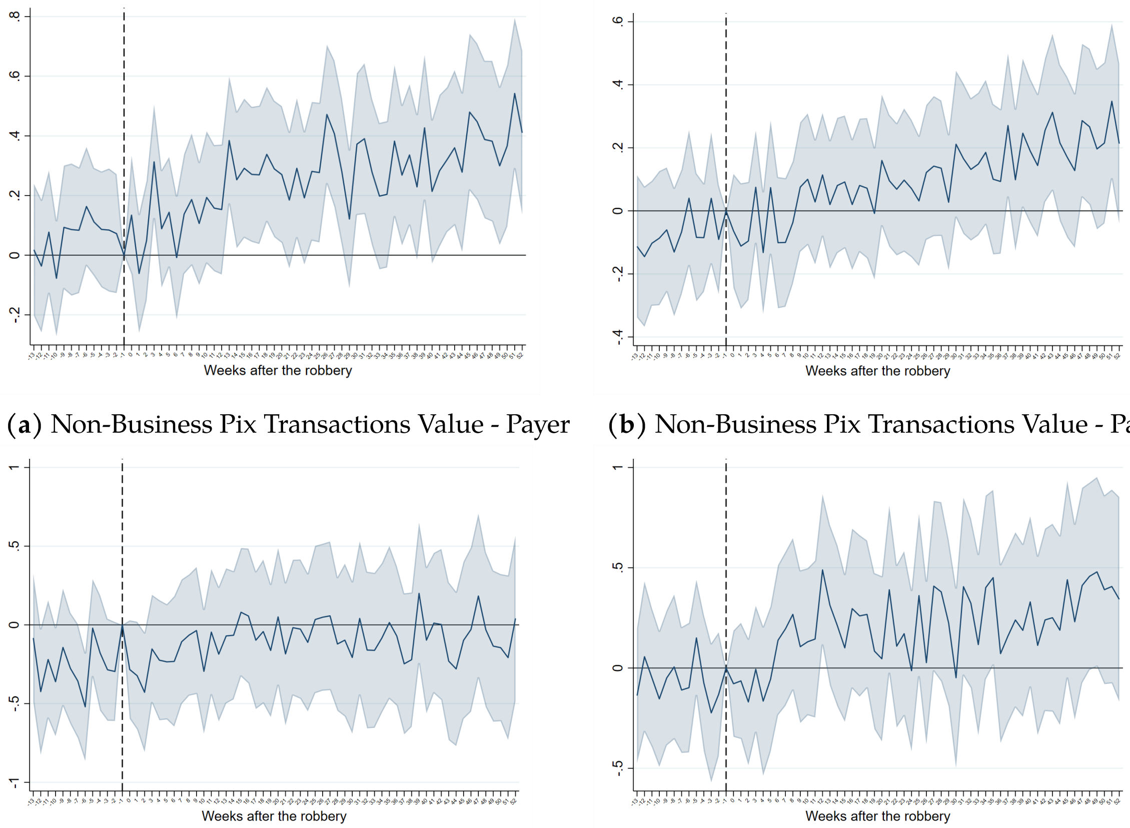
Means of payment and customer channels: Central Bank of Brazil, *Estatísticas de Meios de Pagamentos*, access: https://www.bcb.gov.br/estatisticas/spbadendos.

Pix: Central Bank of Brazil, *Estatísticas do Pix*, access: https://www.bcb.gov.br/estabilidadefinanceira/estatisticasPix.

A2 Robustness

A2.1 Bank-municipality dynamic effects

Figure A4: Bank Robberies and Digital Banks Pix Transactions

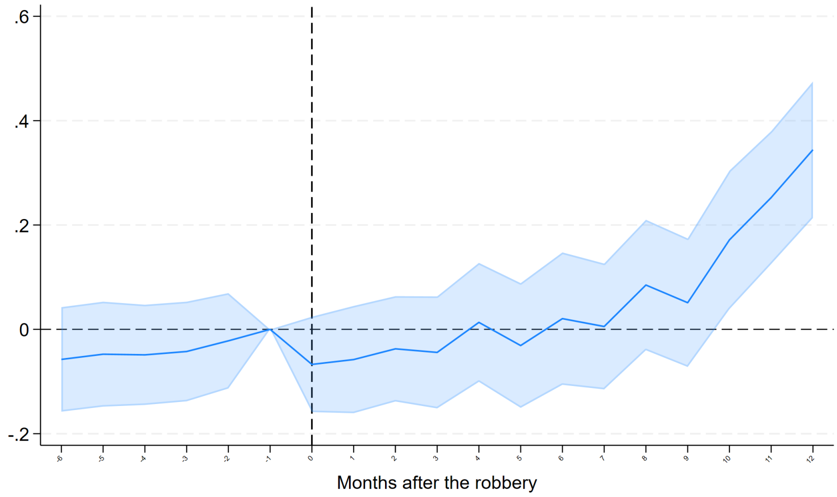


(**a**) Non-Business Pix Transactions Value - Payer (**b**) Non-Business Pix Transactions Value - Payee

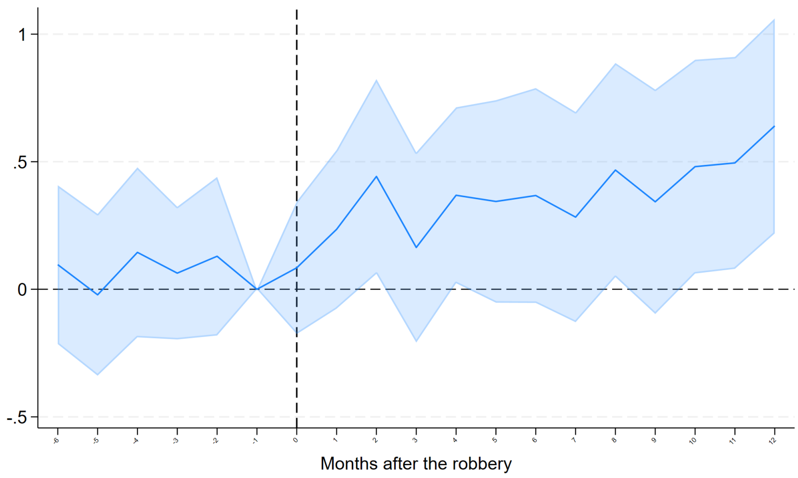
(**c**) Business Pix Transactions Value - Payer (**d**) Business Pix Transactions Value - Payee

Notes: The figures report results from the estimation of a dynamic version Equation 2. We plot the spillover effects for digital institutions. The sample is restricted to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We report 95% confidence intervals based on standard errors clustered at the municipality level. All specifications include municipality and week fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. We use the inverse hyperbolic sine transformation of the original dependent variable. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5.

Figure A5: Bank Robberies and Digital Banks Credit Origination



(**a**) Households Credit Originations Value



(**b**) Firms Credit Originations Value

Notes: The figures report results from the estimation of a dynamic version Equation 2. We plot the spillover effects for digital institutions. The sample is restricted to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We report 95% confidence intervals based on standard errors clustered at the municipality level. All specifications include municipality and week fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. We use the inverse hyperbolic sine transformation of the original dependent variable. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5.

A2.2 Unmatched sample, different controls and weights

Table A6: Cash Inventory and Deposits

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Cash Inventory						
Post Robbery	-0.39***	-0.38***	-0.40***	-0.39***	-0.39***	-0.38***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Post Robbery×(Branches≤Med)	-2.49***	-2.51***	-2.48***	-2.51***	-2.49***	-2.51***
	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)	(0.46)
Observations	169,880	169,814	165,810	165,810	165,810	165,810
R^2	0.80	0.80	0.79	0.79	0.82	0.82
Panel B: Deposits						
Post Robbery	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Post Robbery×(Branches≤Med)	0.02	0.02	0.03	0.02	0.03	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	169,751	169,685	165,686	165,686	165,686	165,686
R^2	0.98	0.98	0.98	0.98	0.99	0.99
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
3G Internet Cov.×Month FE	No	Yes	No	Yes	No	Yes
Sample	All	All	CEM	CEM	CEM	CEM
Weights	No	No	No	No	CEM	CEM
Municipalities	3,035	3,035	2,966	2,966	2,966	2,966
Treated municipalities	455	455	446	446	446	446

Notes: The table presents estimates of Equation 1. In all regressions, the post-robbery window has a length of 12 months and the pre-robbery window has a length of 6 months. We consider all robberies that caused the destruction of branches between 2018 and 2021 and all municipalities that have an active branch (that is, municipalities that have only service stations or that do not have any bank establishment are not included due to lack of data). In Panel A, the dependent variable is the inverse hyperbolic sine transformation of the cash inventory of all branches in a given municipality; in Panel B, the natural logarithmic of the stock of deposits of all branches in a given municipality. In columns 1 and 2, we use the entire sample; in columns 3-6, we use the Coarsened Exact Matching (CEM) sample described in Section 2.5. In columns 1-4, we estimate an OLS regression; in columns 5-6, we estimate a WLS regression using the CEM weights. Standard errors are clustered at the municipality level. Branches≤Med is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

Table A7: Pix Usage

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Number of Pix transactions						
Post Robbery	-0.08**	-0.05	-0.08**	-0.05	-0.06	-0.03
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Post Robbery$\times$(Branches$\leq$Med)	0.32***	0.26***	0.31***	0.26***	0.32***	0.25***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	455,615	455,615	448,028	448,028	448,028	448,028
R^2	0.99	0.99	0.99	0.99	0.99	0.99
Panel B: Value of Pix transactions						
Post Robbery	-0.07**	-0.03	-0.06*	-0.03	-0.04	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Post Robbery$\times$(Branches$\leq$Med)	0.24***	0.17***	0.24***	0.17***	0.24***	0.16***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	455,615	455,615	448,028	448,028	448,028	448,028
R^2	0.96	0.97	0.96	0.96	0.97	0.97
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
3G Internet Cov.$\times$Week FE	No	Yes	No	Yes	No	Yes
Sample	All	All	CEM	CEM	CEM	CEM
Weights	No	No	No	No	CEM	CEM
Municipalities	4,199	4,199	4,129	4,129	4,129	4,129
Treated municipalities	48	48	47	47	47	47

Notes: The table presents estimates of Equation 1. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. In Panel A (B), the dependent variable is the inverse hyperbolic sine transformation of the total number (value) of Pix transactions in a given municipality. In columns 1 and 2, we use the entire sample; in columns 3-6, we use the Coarsened Exact Matching (CEM) sample described in Section 2.5. In columns 1-4, we estimate an OLS regression; in columns 5-6, we estimate a WLS regression using the CEM weights. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Branches$\leq$Med is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

A2.3 Poisson regressions

Table A8: Cash Inventory and Deposits

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Cash Inventory						
Post Robbery	0.13	0.12	-0.04***	-0.04***	-0.04***	-0.03***
	(0.08)	(0.08)	(0.01)	(0.01)	(0.01)	(0.01)
Post Robbery $\times$ (Branches$\leq$Med)	-0.57***	-0.58***	-0.41***	-0.42***	-0.41***	-0.42***
	(0.10)	(0.10)	(0.06)	(0.06)	(0.06)	(0.06)
Observations	169,141	169,075	165,071	165,071	165,071	165,071
Panel B: Deposits						
Post Robbery	0.04*	0.04*	-0.00	-0.00	-0.01	-0.01
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Post Robbery $\times$ (Branches$\leq$Med)	-0.04	-0.04	0.00	0.00	0.00	0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	169,847	169,781	165,777	165,777	165,777	165,777
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
3G Internet Cov.$\times$ Time FE	No	Yes	No	Yes	No	Yes
Sample	All	All	CEM	CEM	CEM	CEM
Weights	No	No	No	No	CEM	CEM
Municipalities	3,035	3,035	2,966	2,966	2,966	2,966
Treated municipalities	455	455	446	446	446	446

Notes: The table presents results from the estimation of Poisson regressions. In all regressions, the post-robbery window has a length of 12 months and the pre-robbery window has a length of 6 months. We consider all robberies that caused the destruction of branches between 2018 and 2021 and all municipalities that have an active branch (that is, municipalities that have only service stations or that do not have any bank establishment are not included due to lack of data). In Panel A, the dependent variable is the cash inventory of all branches in a given municipality; in Panel B, the stock of deposits of all branches in a given municipality. In columns 1 and 2, we use the entire sample; in columns 3-6, we use the Coarsened Exact Matching (CEM) sample described in Section 2.5. In columns 1-4, we estimate an OLS regression; in columns 5-6, we estimate a WLS regression using the CEM weights. Standard errors are clustered at the municipality level. Branches$\leq$Med is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

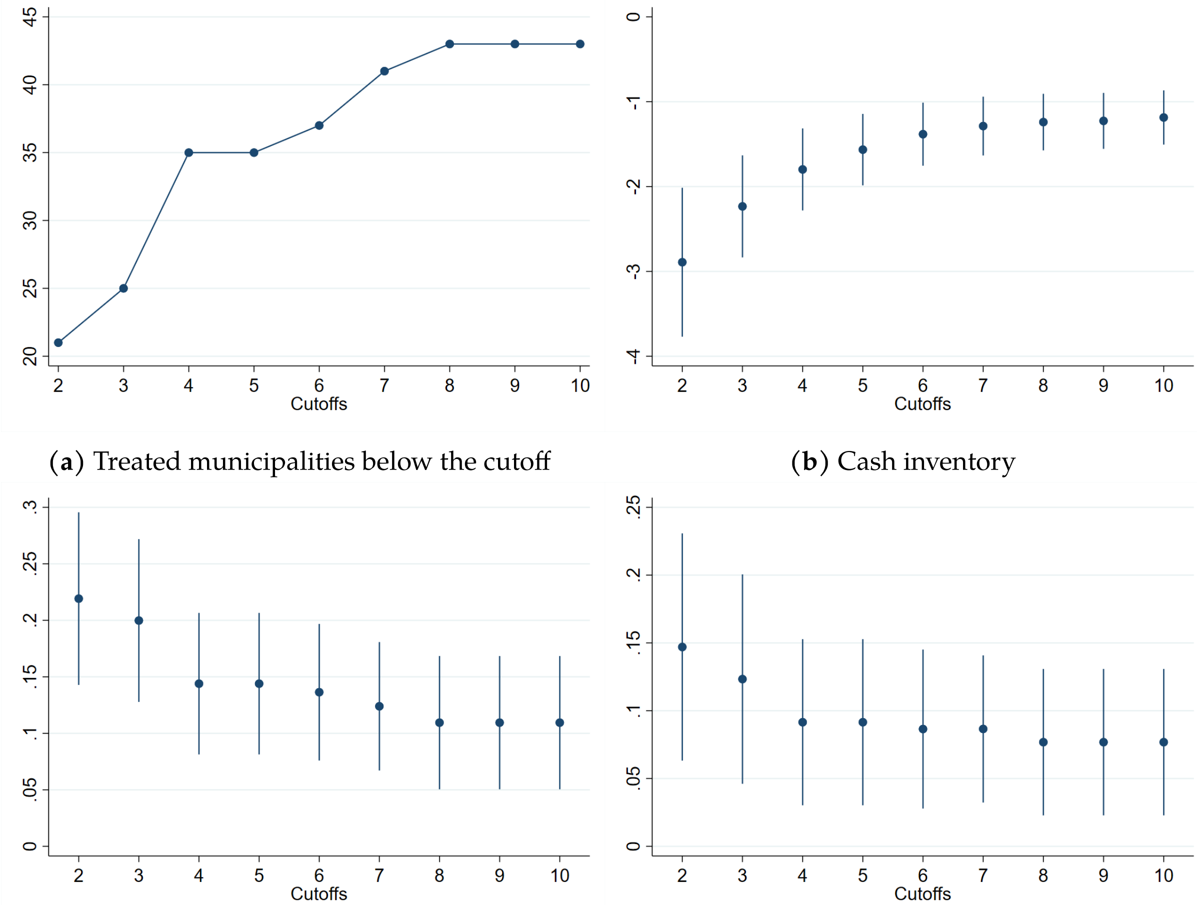
Table A9: Pix Usage

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Number of Pix transactions						
Post Robbery	-0.05	-0.01	-0.08**	-0.04*	-0.01	0.00
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)
Post Robbery $\times$ (Branches$\leq$Med)	0.44***	0.22***	0.44***	0.25***	0.45***	0.22***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Observations	455,615	455,615	448,028	448,028	448,028	448,028
Panel B: Value of Pix transactions						
Post Robbery	0.01	0.03**	-0.02	0.01	0.03	0.04**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)
Post Robbery $\times$ (Branches$\leq$Med)	0.37***	0.18***	0.37***	0.21***	0.38***	0.17***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	455,615	455,615	448,028	448,028	448,028	448,028
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
3G Internet Cov. $\times$ Time FE	No	Yes	No	Yes	No	Yes
Sample	All	All	CEM	CEM	CEM	CEM
Weights	No	No	No	No	CEM	CEM
Municipalities	4,199	4,199	4,129	4,129	4,129	4,129
Treated municipalities	48	48	47	47	47	47

Notes: The table presents results from the estimation of Poisson regressions. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. In Panel A (B), the dependent variable is the total number (value) of Pix transactions in a given municipality. In columns 1 and 2, we use the entire sample; in columns 3-6, we use the Coarsened Exact Matching (CEM) sample described in Section 2.5. In columns 1-4, we estimate an OLS regression; in columns 5-6, we estimate a WLS regression using the CEM weights. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Branches$\leq$Med is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

A2.4 Heterogeneity by the number of local bank establishments: alternative cut-offs

Figure A6: Bank Robberies and Pix Users by Transaction Type



(a) Treated municipalities below the cutoff

(b) Cash inventory

(c) Number of Pix transactions

(d) Value of Pix transactions

Notes: Figure (a) reports the number of treated municipalities in the post-Pix period where the number of branches is below the cutoff. Figures (b), (c), and (d) report results from the estimation of Equation 3 for different cutoffs. We point estimates of the coefficient δ_2, that is, effects in municipalities where the number of branches is below the cutoff. We report 95% confidence intervals based on standard errors clustered at the municipality level. All specifications include municipality and week fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. We use the inverse hyperbolic sine transformation of the original dependent variable. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5.

A2.5 Stacked difference-in-differences

Table A10: Bank Robberies and Pix Usage: Stacked Difference-in-Differences

	(1)	(2)	(3)	(4)
	Quantity		Value	
Post Robbery	0.081***	-0.033	0.058**	-0.017
	(0.030)	(0.031)	(0.026)	(0.026)
Post Robbery×(Branches≤Median)		0.246***		0.163***
		(0.049)		(0.048)
Municipality×Cohort FE	Yes	Yes	Yes	Yes
Week×Cohort FE	Yes	Yes	Yes	Yes
Week×3G Coverage×Cohort FE	Yes	Yes	Yes	Yes
Observations	7,222,808	7,222,808	7,222,808	7,222,808
Municipalities	4,129	4,129	4,129	4,129
Treated Municipalities	47	47	47	47
R^2	0.994	0.994	0.978	0.978

Notes: In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. In columns 1-2 (3-4), the dependent variable is the inverse hyperbolic sine transformation of the quantity (total value) of intra-municipality Pix transactions in the municipality. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Branches≤Median is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

A3 Other outcomes

A3.1 Aggregate credit origination

Table A11: Bank Robberies and Aggregate Credit Origination

	(1)	(2)	(3)	(4)
	Household		Firms	
Post Robbery	-0.009	-0.010	-0.058**	-0.061**
	(0.009)	(0.009)	(0.024)	(0.026)
Post Robbery×Post Pix		0.002		0.015
		(0.015)		(0.044)
Post Robbery×(Branches≤Median)	0.010	0.005	0.099**	0.092*
	(0.012)	(0.013)	(0.049)	(0.054)
Post Robbery×(Branches≤Median)× Post Pix		0.025		0.031
		(0.024)		(0.078)
Municipality FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Month×3G Internet Cov. FE	Yes	Yes	Yes	Yes
Observations	253,054	253,054	253,054	253,054
Municipalities	4,636	4,636	4,636	4,636
Affected Municipalities	564	564	564	564
R^2	0.986	0.986	0.882	0.882
Below Effects (p-value)	0.952	0.589	0.345	0.509
Above Effects Post-Pix (p-value)		0.575		0.276
Below Effects Post-Pix (p-value)		0.245		0.196

Notes: The table presents estimates of Equation 1. In all regressions, the post-robbery window has a length of 12 months and the pre-robbery window has a length of 6 months. The dependent variables are the inverse hyperbolic sine transformation of the total value of new loans to households (firms) in a given municipality-month. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure. Branches≤Median is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.

A3.2 Other digital payments

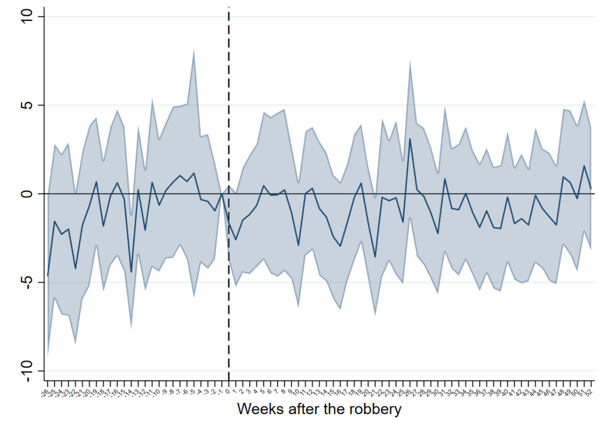
Table A12: Bank Robberies and Other Payment Methods

	(1) Credit Card	(2) Debit Card
Post Robbery	-0.050***	-0.016
	(0.008)	(0.014)
Post Robbery×Post Pix	-0.006	-0.012
	(0.014)	(0.025)
Post Robbery×(Branches≤Median)	0.085**	0.166***
	(0.034)	(0.036)
Post Robbery×(Branches≤Median)×Post Pix	-0.035	-0.088*
	(0.045)	(0.047)
Municipality FE	Yes	Yes
Week FE	Yes	Yes
Week×3G Coverage FE	Yes	Yes
Observations	1,094,524	1,094,524
Municipalities	4,636	4,636
Affected Municipalities	564	564
R^2	0.972	0.963

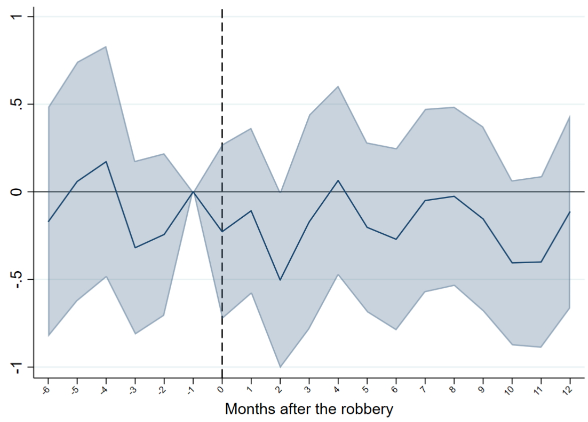
Notes: In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. The dependent variable is the inverse hyperbolic sine transformation of the total value transactions in the municipality. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Branches≤Median is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities

A3.3 Homicides and COVID-19 incidence

Figure A7: Bank Robberies, Homicides and COVID-19 Incidence



(**a**) Effects of bank robberies on COVID-19 Cases (per 100.000 people)



(**b**) Effects of bank robberies on homicides (per 100.000 people)

Notes: The figures report results from the estimation of Equation 1. We report 95% confidence intervals based on standard errors clustered at the municipality level. All specifications include municipality and time fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. We use the inverse hyperbolic sine transformation of the original dependent variable. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5.

A3.4 Payroll loans

Table A13: Payroll Loans (Origination)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total Payroll Credit		Retiree Payroll Credit		Public Employees Payroll Credit		Private Employees Payroll Credit	
Post Robbery (Direct Effects)	-0.263**	-0.267**	-0.267**	-0.251**	-0.163	-0.128	-0.020	0.016
	(0.105)	(0.117)	(0.105)	(0.118)	(0.154)	(0.166)	(0.137)	(0.146)
Post Robbery (Direct Effects)×Post Pix		0.033		0.081		-0.262		-0.272
		(0.132)		(0.187)		(0.187)		(0.349)
Spillover Effects×Branch-based	0.007	0.008	0.016	0.017	0.006	0.013	0.005	0.008
	(0.016)	(0.017)	(0.014)	(0.015)	(0.012)	(0.013)	(0.007)	(0.008)
Spillover Effects×Branch-based×Post Pix		-0.003		-0.004		-0.042		0.017
		(0.039)		(0.035)		(0.032)		(0.020)
Spillover Effects×Digital	0.045	0.044	0.030	0.037	0.017	0.009	0.000	-0.000
	(0.029)	(0.033)	(0.026)	(0.029)	(0.012)	(0.015)	(0.000)	(0.000)
Spillover Effects×Digital×Post Pix		0.002		-0.021		0.023		0.001
		(0.058)		(0.055)		(0.023)		(0.000)
Muni×Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month×3G Coverage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month×Institution FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.783	0.783	0.784	0.784	0.695	0.695	0.503	0.503
# Observations	25,344,364	25,344,364	25,344,364	25,344,364	25,344,364	25,344,364	25,344,364	25,344,364

Notes: The table presents estimates of Equation 2 augmented with interactions with dummies that take the value one after the Pix launch. The sample is restricted to municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities. In all regressions, the post-robbery window has a length of 52 weeks and the pre-robbery window has a length of 13 weeks. We consider all robberies that occurred between February 2021 (two months after the launch of Pix) and December 2021 and caused the destruction of branches. The dependent variable is the inverse hyperbolic sine transformation of the value of new loans. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5.

A3.5 Real outcomes

Table A14: Hirings and Firings

	(1)	(2)	(3)	(4)
	Firings		Hirings	
Panel A: All sectors				
Post Robbery	-0.01	0.02*	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Post Robbery×(Branches≤Median)	0.00	-0.04	-0.00	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)
Observations	231,312	231,312	231,312	231,312
R^2	0.91	0.91	0.92	0.90
Panel B: Retail and restaurants				
Post Robbery	-0.02	-0.01	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Post Robbery×(Branches≤Median)	0.03	0.02	-0.01	0.01
	(0.03)	(0.03)	(0.03)	(0.03)
Observations	231,312	231,312	231,312	231,312
R^2	0.90	0.92	0.92	0.91
Firm size	All	Small	All	Small
Municipality FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
3G Internet Cov.×Month FE	Yes	Yes	Yes	Yes

Notes: The table presents estimates of Equation 1. In all regressions, the post-robbery window has a length of 12 months and the pre-robbery window has a length of 6 months. We consider all robberies that caused the destruction of branches between 2018 and 2021. Panel A uses the number of firings and hirings at the municipality-month level for firms in all sectors, while Panel B restricts the data for firings and hirings in the retail and restaurant sectors. The data come from extractions of the *Relação Anual de Informações Sociais* (RAIS), a dataset from the Ministry of Labor that contains all the hirings and firings in the formal sector. The data range from 2017 to 2021 (the last year available at the moment of the extraction). In columns 1 and 3, we consider firms of all sizes (as measured by the number of workers) in the aggregation at the municipality-month level; in columns 2 and 4, we only use small firms in the aggregation (firms with less than 20 employees). In all regressions, the dependent variable is the inverse hyperbolic sine transformation of the original variable. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure described in Section 2.5. Branches≤Median is a dummy variable that takes the value one for municipalities with at most two branches, where two is the median of the distribution of the number of bank branches across all municipalities.