Banks' Physical Footprint and Financial Technology Adoption*

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Abstract

Do physical bank branches moderate the diffusion of digital payment technologies? Does the diffusion of an efficient and inclusive digital payment technology allow fintechs to increase their presence? To answer these questions, we leverage bank heists that use explosives and render branches temporarily inoperable. We provide evidence that these attacks are not associated with local crime trends and that they deplete the branches' cash inventory. Moreover, we show that they lead to persistent increases in digital payments usage and that a smaller cash dependence boosts digital institutions' growth not only in payments but also in credit markets.

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1 Introduction

The emergence of fintechs and the proliferation of new technologies and products have been transforming the financial industry. At the same time, traditional financial services providers are shifting their business model from in-person services provided through a branch network to digital, internet-based services (Vives, 2019).[1] These trends can foster competition and the democratization of financial services (Philippon, 2016, 2019). A burgeoning literature has started to document the consequences of the digital disruption in banking and the drivers of the adoption of financial technologies. In this paper, we investigate how the presence of physical branches influences the financial technologies used by consumers and firms, and the potential implications for the expansion of digital institutions and competition in the banking industry.

We focus on payment technologies. A key function of bank branches is the provision of payment services, in particular by storing and distributing currency. The attractiveness of cash as a means of payment increases in locations 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 (Alvarez et al., 2022; Crouzet et al., 2023; Higgins, 2022). 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, the presence of physical branches can induce a locality to use more cash even when new, welfare-enhancing technologies become available. Such reliance on cash can reduce the competitiveness of institutions that only operate digitally and do not have the physical infrastructure necessary to support cash deposits and withdrawals. In the presence of economies of scope between the provision of payment and credit services, digital institutions might see negative spillovers from local cash dependence to their competitiveness in credit markets.

We explore the consequences of temporary and unexpected branch closures, which disrupt in-person services and, among other things, increase cash handling costs. In general, the suspension of branch services is the result of banks' operating decisions and can reflect unobserved factors that also determine technology adoption. For instance, banks might close branches in places 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 induce the adoption of digital payment technologies, especially among individuals, and we document important spillovers for digital financial institutions.

Brazil is an appealing laboratory in which to study this topic. First, although Brazil

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

is an emerging economy, its financial institutions are sophisticated and offer a variety of payment services and financial products. The use of those technologies is considerable. For instance, in 2019, purchases with credit, pre-paid, and debit cards amounted to 23.8% of GDP, and the country had 53 point-of-sale terminals per 1,000 inhabitants (11.2 million), a number larger than in some developed countries, such as Canada (47) and the United Kingdom (45). At the same time, traditional payment methods remain important: in the same year, cash withdrawals amounted to 44.8% of GDP.[2] Second, due to security concerns, the majority of ATMs are located inside bank establishments. As a result, branches play an instrumental in the provision of cash services. Third, a criminal activity that leads to a halt in the provision of in-person branch services has been afflicting the country. Organized crime groups target branches, mostly in small and medium-sized cities, through "hit-and-run" raids. They use explosives to access all the cash stored in the vault and ATMs. The attacks occur in the dead of night when the streets are empty and there is less police presence; immediately afterward, the groups flee the region. Usually, this activity results in the complete destruction of the branch and the interruption of in-person services for a couple of months.

Anecdotal evidence collected in newspaper articles suggests that the abrupt closure of branches has adverse consequences for firms and individuals, especially in small municipalities that have one or two branches. In these locations, the robbery events force individuals to travel long distances to access cash, which reduces its appeal as a means of payment.[3] This type of bank heist requires skilled personnel, meticulous training and planning, and an expensive apparatus. The attacks are carried out by non-local organized groups and are not associated with increases in other criminal activities or changes in local unobserved variables that could correlate with adoption and usage decisions. These features make the setting particularly attractive to answer the research questions we pose. Using weekly and monthly data, we implement an event-study difference-in-differences empirical strategy around these criminal events using municipalities that are not affected by such crime as a control group.

We first show that the shock has a significant impact on branches' cash inventory. Compared to branches in control municipalities, treated branches have virtually no cash right after an attack (-97%). Treated branches remain with a lower cash inventory for at least six months, suggesting that the affected localities become less cash-dependent even when the branches reopen. We provide evidence that there are some minor short-lived spillover effects on cash inventories for non-robbed branches in the same location, which are likely driven by higher demand from clients of the affected branches. We show that these crimes have minor effects on the stock of deposits of the treated branches, at least in the short run, indicating that the main consequence of the robberies is the depletion of the amount of cash stored in the branches. Next, we investigate whether branch explosions and local criminal activity are connected. We

[2]Sources: Brazilian Central Bank and Bank for International Settlements.

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

show that the shocks are neither followed nor preceded by an increase in homicides or robberies, 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 then study the effects on payment technology adoption. We focus on Pix, an instant payment technology that was launched in November 2020 by the Central Bank of Brazil (BCB). Pix is free of charge to individuals, easy to use (alias-based), available 24/7, and only requires an account in a bank or payment institution and a connection to the internet. Before Pix, alternative options were costlier, not instant, or less user-friendly. Between its launch and December 2021 (a 13-month period), 96 million individuals (54% of the adult population) made at least one transfer using Pix (Central Bank of Brazil, 2021). In January 2022, users made more than 1.3 billion transactions, totaling BRL 640 billion (USD 123 billion). Despite its success, around 71 million adults (40% of the adult population) still do not use any electronic system to make transfers.

We document an increase in intra-municipality Pix transactions in the aftermath of robberies that cause the destruction of branches. We find that treated places experienced a 9.2% higher number of Pix transactions, while the total value of Pix payments was 7.6% higher. These effects are smaller and become non-statistically significant as the number of alternative branches to perform cash withdrawals increases.[4] We also document an increase in the number of Pix users, pointing to results being driven by both intensive and extensive margin effects. We focus on intra-municipality transactions (in which the payer and payee are located in the same municipality), as short-distance Pix transactions are more likely to be substitutes for cash. Inspecting the dynamics of the effects, we note that Pix usage grows for roughly 2 months after the event and remains flat (at a higher value) thereafter, which shows that temporary branch closures have persistent effects. We further show that Pix usage increases among individuals acting as payers and payees, while for firms, the increase is only present when they act as payees. This pattern, which is not unique to Pix (Alvarez et al., 2022), is consistent with cash not being the prevalent method in business-to-business transactions before the shock; alternatively, it is also consistent with Pix not being the best substitute for cash in those types of transactions, showing that gains and costs from technology adoption are heterogeneous across economic agents (Suri, 2011).

We show that, beyond being a substitute for cash, Pix transactions were substitutes for more traditional electronic payment methods. Our results show that, before Pix, individuals used debit cards and the available electronic bank transfer method (known as TED) to weather the cash provision shock. However, after the introduction of Pix, they increase the use of Pix and debit cards, but TED transfers do not grow. We also document the effects on long-distance transactions. Due to larger transaction costs, such transactions were unlikely to be carried out by cash in the first place. Moreover,

[4] This result provides further evidence that the mechanism that underlies Pix adoption increases in these localities is the availability of cash and not the fear of using cash after the robbery.

the shock hits more severely only the side of the transaction that is in the municipality where the exploded branch is located. Using inter-municipality transfers (in which payer and payee are in different municipalities) as a proxy for those transactions, we show that the number of Pix payments to or received from other municipalities increases by about 7% after the event.

Finally, we document spillovers for institutions that operate in the treated municipalities but do not have a branch that was attacked. Pix is accessed through banks' mobile apps or websites. As digital services are not disturbed by the shock and changing banks impose costs on users, if the robbed banks were competitive in the provision of digital services, we would expect customers to keep using them to make Pix transactions. However, we show that the quantity and value of Pix transactions and the number of users of non-robbed private branch-based banks and digital institutions increase after a bank robbery in the municipality. The increase in Pix usage is especially important for digital institutions. These institutions do not have a network of physical branches and ATMs, and customers who need to withdraw or deposit cash usually need to use the network of other institutions at a cost. As a result, a greater local reliance on cash severely reduces the ability of these institutions to provide payment convenience.

Spillovers are not limited to payment services: unaffected institutions also provide more credit after the shock. We show that the provision of loans increases in digital institutions while it decreases in affected branch-based banks, with non-significant effects on local aggregated credit. This result suggests the existence of complementarities between credit and payment services, which can be explained, among other factors, by an increase in the availability of hard information. Importantly, we provide evidence that Pix adoption mediates the credit spillover effects. The increase in digital institutions' household credit is three times larger after Pix's introduction: the effect before Pix is 4.4% while after Pix it is 11.9%. Moreover, branch operation shocks do not increase digital institutions' business loans before Pix; however, such effects become significant during the Pix period and amount to a 15.5% increase. The results show that once the local dependence on cash is reduced, and a suitable substitute for cash is available, digital institutions can expand, possibly enhancing competition in the local financial market.

Our paper ties into recent literature that explores large shocks that fuel the adoption of alternative technologies. Payment technologies are characterized by two-sided markets that display network externalities. The value of a particular payment method for an agent, and thus the decision to embrace it, depends on how disseminated this method is among other users. This network externality can spark coordination failures and hamper the diffusion of alternative technologies (Alvarez et al., 2022; Buera et al., 2021; Huynh et al., 2022; Katz and Shapiro, 1986; Rochet and Tirole, 2006; Rosenstein-Rodan, 1943). Similarly, fixed costs (such as learning costs) and lack of trust and information can also dampen the expansion of new alternatives (e.g., Bachas et al., 2018;

Breza et al., 2020; Gupta et al., 2020). As a result, previous research has shown that events that temporarily increase the cost of the currently mostly used technology can induce agents to jointly and permanently adopt an alternative one (Chodorow-Reich et al., 2020; Crouzet et al., 2023; Higgins, 2022; Lahiri, 2020).

The events we explore, by reducing the attractiveness of cash, share similar features with those studies. However, in those papers, the functioning of local branches is not affected, that is, the provision of most branch services remains intact, while in ours there is a significant disruption. This feature allows us to study to what degree the physical footprint of banks influences the spread of new technologies and how these technologies mediate the presence of digital institutions. This is important as a strand of recent research documents the benefits that new payment technologies can bring to consumers and firms.[5] On the other hand, access to new technologies remains unequal (Saka et al., 2022; World Bank, 2016). Individuals that are less educated, poorer, and older can be left out of the digitization of services. Survey evidence also indicates a fintech gender gap (Chen et al., 2021). By facilitating the use of cash and providing in-person services, branches play an important role in the presence of such a "digital divide" (Alvarez and Argente, 2022; Jiang et al., 2022).

This paper also builds on the literature that studies the consequences of branch closures. Bonfim et al. (2021), Martín-Oliver et al. (2020), and Nguyen (2019), among others, document negative effects on credit and firm survival, with larger effects on small firms. A related paper is Choi and Loh (2022), which studies the effects of permanent ATM closures on digital banking adoption using data from a single bank. By leveraging a unique shock that is exogenous to banks' decisions, we add to this literature by providing evidence that the temporary closure of branches positively affects the adoption of digital payment technologies. Moreover, we document important spillovers for non-affect banks (including fintechs), which increase their presence not only in payment markets but also in credit markets.

Our results provide further evidence that digital institutions are better equipped to provide digital payment services (D'Andrea and Limodio, 2020; Core and De Marco, 2021; Kwan et al., 2021). We show that digital institutions grow in a given locality when the use of digital payments increases. In other words, the reliance on cash and the need for physical infrastructure to enable its use can be an obstacle to the expansion of institutions that only provide digital payment services, slowing down potential benefits they can bring, including innovative products and more competition in an industry that in general displays high levels of concentration (Philippon, 2016, 2019).[6]

[5]Financial technologies can affect transaction costs (Bachas et al., 2018), savings (Bachas et al., 2020), consumption (Agarwal et al., 2020), risk-sharing (Jack and Suri, 2014; Riley, 2018), availability of hard information and credit access (Dalton et al., 2023; Berg et al., 2020; Ghosh et al., 2021; Parlour et al., 2020), occupational choice and labor reallocation (Suri and Jack, 2016), business creation and growth (Agarwal et al., 2020; Beck et al., 2018; Hau et al., 2021); and crime and tax evasion (Alvarez et al., 2021; Gandelman et al., 2019; Lahiri, 2020; Rogoff and Rogoff, 2017; Wright et al., 2017).

[6]In a sample of 123 countries, the average share of assets held by the 5 largest banks was 80.4% in

2 Empirical Setting

2.1 The Banking and Payments Industry in Brazil

The financial industry in Brazil is concentrated. 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 remain large in 2021 (assets, 68.6%; credit, 63.7%).[7] Lack of competition, among other factors, is believed to be behind relatively large spreads and fees. In 2021, the revenue from fees of the five largest commercial banks amounted to 78.5% of all fees levied in the financial system.

The banking industry has been digitalizing and reducing its physical footprint in recent years. The number of branches dropped by 4,903 between 2016 and 2021, a 21.7% reduction. As a result, the number of branches per 100,000 inhabitants decreased from 11 to 8.3, and the share of municipalities not served by a branch increased from 36% to 43.5%. The number of service stations with an ATM per 100,000 inhabitants also decreased sharply in the same period, from 16.2 to 12. Part of the reduction in the number of branches was offset by an increase in service stations, which nonetheless provide fewer services, especially large cash payments and withdrawals (small-value cash operations can be carried out in an ATM). Service stations are branch subsidiaries with simpler and cheaper structures, as, for instance, they do not need a vault, security (guards, metal detector), and certain employees (manager, treasurer). The number of service stations increased by 3,692 between 2016 and 2021, mostly driven by credit unions, which are responsible for 64% of this expansion. The share of municipalities with neither a branch nor a service station increased from 6.6% to 8.3% during this period.

The digitalization trend is reflected in the customer channels 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 acting 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 known as *boletos* (22.3%), followed by 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 many ATMs are located inside branches due to security concerns, the temporary clo-

2021 (World Bank Global Financial Development Database).

[7] Reference dates December 2016 and September 2021. The sample excludes the national development bank (BNDES) and includes all financial institutions that grant loans, including credit unions and non-deposit-taking lenders.

sure of a branch can be very disruptive, increasing the costs of cash withdrawals and deposits, and at the same time increasing costs to monitor balances and apply for loans.

Regarding the payment system in Brazil, apart from cash, prior to 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 can be used by both firms and individuals. 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, and the payer can settle the transaction at a branch, or using an ATM or a digital channel such as internet or mobile banking. It is common in person-to-business and business-to-business transactions because they are easily integrated into financial management softwares and they allow for flexibility in payment dates, which is convenient due to the common practice of trade credit extension in business-to-business transactions. Table A2 of the Online Appendix describes the characteristics of the main means of carrying out transfers, and Table A3 shows that in 2019 debit cards accounted for 24.8% of the number of transactions, followed by credit cards (22%) and *boletos* (17.8%). In terms of value transacted, TEDs account for 41.3%, followed by wire transfers between accounts in the same bank (23.2%) and *boletos* (15.8%).

2.2 The Introduction of Pix

In November 2020 the BCB launched a new instant payment system called Pix.[8] The system was created in an attempt to promote the digitalization of payments, competition among payment service providers, better user experience and reduced costs. Pix allows payments from all types of accounts and is available 24/7. It is a real-time gross settlement (RTGS) 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.

Pix has two interesting 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, i.e., banks and payment institutions can only charge firms. The mandatory participation of large banks and the absence of fees for individuals were designed to promote Pix usage. Prior to Pix, the available options were costlier, less user-friendly, and not instant.[9]

[8]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)

[9]The average TED fee per transaction is around BRL 17 in October 2020 (around USD 3). Source:

As of April 2022, 117.5 million individuals (around 55% of the population) and 9 million firms (around 47% of active firms) had registered to use the system.[10] In Table A4 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). In terms of quantities, possibly because of its absence of fees, speed and simplicity, 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. Survey evidence indicates that Pix is less disseminated among poor and less educated individuals.[11] In terms of value transacted, person-to-person transactions represent 36.3% of the total, followed by business-to-business transactions (30.5%).

In Table A5 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 characteristics of the financial sector, municipalities with higher Pix usage per inhabitant have more deposits and branches; their branches have a higher cash inventory and competition for deposits is larger according to the Herfindahl–Hirschman Index.

2.3 Bank Robberies

Brazil has suffered from bank robberies that plunder the cash stored inside bank branches with the use of explosives and/or blowtorches. The raids occur in the dead of night, and, minutes after the action, the criminals flee the targeted city. In general, the heist causes the destruction of the branch (Figure 1), which needs to be refurbished to become operable again.

The raids are carried out by sophisticated organized criminal organizations 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 estimated costs of performing a raid are around BRL 400,000 (around USD 80,000), and it requires the participation of at least 10 people (Aquino, 2009).[12] The level of sophistication and high cost of these operations imply they are unlikely to be carried out by local, amateurish groups, and hence they tend to be unrelated to trends in other crimes.

https://www.bcb.gov.br/estabilidadefinanceira/tarifas_dados.

[10] According to the Ministry of Economy, 18.9 million firms were active in September 2021. According to estimates of the Brazilian Institute of Geography and Statistics (IBGE), Brazil had a population of 213.3 million in 2021. It is important to note, however, that registration does not imply usage.

[11] See the Zetta study *A transformação do Pix para os pagamentos brasileiros*, access: link.

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

Our sample contains records of 810 robberies in 521 municipalities of 15 states that resulted in the destruction of branches between 2018 and 2021.[13] The states in our sample account for 75% of the municipalities (4,168 out of 5,570), 82.3% of the branches, and 81.4% of the national GDP in 2019. The number of robberies has fallen over time: 481 in 2018, 160 in 2019; 93 in 2020; and 76 in 2021.

In Table A9 of the Online Appendix, we show that municipal economic characteristics do not seem to be predictors of such criminal events. However, in Table 1 we show that municipalities that underwent a branch robbery tend to be richer and more populous than those that were not targeted during our sample. In the empirical strategy section, we provide more details on the Coarsened Exact Matching (CEM) procedure that we use to deal with potential identification threats arising from such imbalances.[14]

2.4 Data

Our main dataset is assembled by combining data from several sources and includes information from robberies, branches, and five types of payment methods: Pix, TED, *boleto*, debit cards and credit cards. We also have information on credit coming from the Central Bank of Brazil's credit registry (SCR). Moreover, we use information on mobile internet coverage and municipalities' and financial institutions' characteristics.

Bank robberies. We build a novel dataset with information on bank robberies, including whether criminals use explosives and the degree 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 asked state police departments to provide the data at the municipality level. When state police departments' records do not contain data on the identity of the banks that were robbed and whether the criminals used explosives, we perform an active search on the internet to obtain the information. We exclude the municipalities that had robberies on two different dates.

Bank branch information. The BCB maintains a dataset on bank branches at the municipality-month level known as ESTBAN (*Estatística Bancária Mensal*). ESTBAN includes the location of bank branches and their monthly balance sheets. From balance sheet data, we can observe the stock of deposits, loans, and the physical cash inventory. This dataset does not contain information on flows, such as loan origination.

TED. For TED transactions, we use data from the *Sistema de Transferência de Reservas* (STR) and *Sistema de Transferência de Fundos* (Sitraf). Both STR and Sitraf are real-time gross settlement payment systems that record electronic transactions. The STR is operated by the BCB, while Sitraf is operated by CIP (*Câmara Interbancária de Pagamen-*

[13]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.

[14]In Figure 10 we also show that other criminal activities do not seem to be affected by the bank robberies, corroborating with our identification strategy.

tos).[15] We collect weekly information on the number and value of intra-municipality TED transactions. We do not observe TED transactions between accounts of the same institution (book transfers).

Boleto. *Boleto* payments data come from CIP which operates the SILOC (*Sistema de Liquidação Diferida das Transferências Interbancárias de Ordens de Crédito*), where the *boletos* are cleared. We collect weekly information on the number and value of *boletos* cleared and aggregate the data by the municipality of the payer.

Credit and debit cards. Debit and credit card data come from CIP. This dataset contains card sales amount by firm and is restricted to open arrays.[16] We aggregate this data by municipality and week. We do not have information on the number of transactions, only values.

Pix. The BCB maintains data on Pix transactions. The data contain information on the date of the transaction, value, payer, payee, and payment service provider (PSP). Pix PSPs are either financial (banks) or payment institutions. For simplicity, we will refer to Pix PSPs as simply *institutions*. We collect Pix weekly information at the municipality level and at the municipality-institution level.[17] We classify institutions into 5 types:

- *Branch-based private banks*: private commercial banks with more than 1,000 branches;
- *State-owned commercial banks*: banks controlled by the central or local governments;
- *Digital institutions*: institutions that rely mainly on digital services. This includes private digital commercial banks and payment institutions;[18]
- *Credit unions*: financial institutions that provide credit and financial services to their members, and operate on a local market.
- *Others*: other financial institutions that operate at least partially through some form of non-branch physical presence. These institutions are not fully digital financial institutions.

For our sample, the market share of Pix transactions is concentrated on large banks and digital institutions. Branch-based private banks have a market share of 29%, while state-owned banks' market share is around 24%. Digital institutions have the highest market share, around 37%. These statistics refer to transactions in which either the

[15]The CIP (Interbank Payments Chamber) is a non-profit civil society clearinghouse that is part of the Brazilian Payments System, supervised by the Central Bank of Brazil.

[16]This dataset does not include private label cards or meal vouchers.

[17]In fact, our data is at the Pix *direct* PSP level. Pix direct PSPs are financial or payment institutions that settle Pix transactions directly in the Instant Payments System (SPI). Indirect Pix PSPs settle Pix transactions through a direct PSP. Therefore, data from indirect PSPs are aggregated inside their PSP. As all relevant financial institutions must be direct participants, we believe this is not a relevant issue. More information regarding Pix PSPs can be found at https://www.bcb.gov.br/en/financialstability/pixparticipants.

[18]Non-depository institutions that only provide payment services, including transfer or withdrawal of funds held in payment accounts.

payee or the payer is an individual. For the municipality-level data, we collect information on Pix for:

- Intra-municipality transactions: both payer and payee live in the same municipality;
- Inflow transactions: where the payer is outside and the payee is inside the municipality; and
- Outflow transactions: where the payer is inside and the payee is outside the municipality.

For the municipality-institution level, we consider intra-municipality transactions. Furthermore, we build a balanced panel of municipality-institution-week. In some regressions, we divide Pix transactions by households and firms. Unfortunately, we do not observe Pix transactions between accounts of the same institution. Nevertheless, this is a relatively small fraction of total Pix transactions. Furthermore, we exclude Pix transactions between accounts that belong to the same person or firm.

Credit Registry. The BCB also maintains a credit registry called SCR, which contains data on several types of loans. With this dataset, we are able to build a panel with credit information by municipality x institution x month level. More specifically, we compute the total amount originated and the number of credit clients (households and firms) that receive new loans, for each municipality x institution x month. We exclude from the analysis the so-called "earmarked credit", i.e., the types of credit that the institution cannot freely distribute (e.g., rural credit, real estate financing).

Internet Coverage. The source of information is ANATEL, the Brazilian telecommunications regulator, and includes yearly information on mobile internet coverage at the municipality level. This coverage is heterogeneous across municipalities in Brazil and we use the information on the coverage in 2020, the first year when the data is available.

Sample restriction. We restrict our analysis to municipalities that had at most 10 branches or service stations in 2019. Out of the 5,570 municipalities in Brazil, 5,153 had fewer than 10 branches and service stations. Those are the places where the shock we explore is plausibly more relevant, as in places with a high density of banks it is much easier to use an alternative branch of the same bank. Indeed, the average (median) number of branches in the restricted sample is 1.3 (1), in comparison to 31.3 (20) in places with more than 10 branches or service stations.[19]

2.5 Empirical Strategy

Our empirical strategy consists of difference-in-differences event-studies analyses exploiting quasi-experimental variation arising from bank branch disruptions. Our identification assumption is that treated and non-treated municipalities would follow parallel trends in the absence of the treatment. Although ex-ante heterogeneity does not

[19] In Table 3, we show that effects are indeed smaller in places with more branches.

necessarily invalidate the method, we implement a Coarsened Exact Matching (CEM) technique to obtain a more balanced sample. This method aims at improving efficiency and the plausibility of our identifying assumptions (Blackwell et al., 2009). We perform the matching using measures of 3G internet coverage, municipality area, population, number of households, and GDP in 2019.

As we can see in Table 1, there are some differences between municipalities that suffered a bank robbery and the control group in the unmatched sample. In the unrestricted sample, the municipalities that suffered such crimes tend to be bigger and have better access to 3G internet. After employing the CEM pre-processing and weighting, these differences disappear, and the control and treatment groups become very similar, even across characteristics that were not directly included in the matching procedure, such as homicide rates, measures of financial development, and characteristics of the local economy. As these differences might be correlated with time-varying patterns of technology adoption, we proceed in the rest of the paper with the matched sample of municipalities and, in the Online Appendix, we provide results for the unweighted and unmatched samples.

We start by analyzing branch-level outcomes. We check the effects on the stock of branch cash holdings and deposits. Our specification also allows us to shed some light on the spillover effects of such crimes for other bank branches that operate in the same municipality. Using bank-municipality-month data, we estimate the following specification:

$$y_{bmt} = \alpha_{bm} + \alpha_{bt} + \delta PostRobBank_{bmt} + \gamma PostRobMun_{bmt} + \beta_t \times 3G\_Cov_m + \epsilon_{bmt} \quad (1)$$

where b represents a bank, m the municipality and t month. $PostRobBank_{bmt}$ is a dummy variable that takes the value 1 after the bank b experiences a branch explosion in municipality m, while $PostRobMun_{bmt}$ takes the value 1 if bank b does not experience a branch explosion, but another bank in its municipality m experienced a branch destruction before time t. The variable $3G\_Cov_m$ is a continuous variable on the percentage of municipal residents covered by mobile internet. To be able to use as many robbery events as possible during the Pix period, which is relatively short, we focus on a post window of six months. The coefficient δ captures direct effects, while the coefficient γ captures spillover effects. We control for time-varying heterogeneity at the bank level (bank-time fixed effects, α_{bt}), time-varying heterogeneity on municipality 3G coverage (time dummies interacted with 3G coverage), and time-invariant bank-municipality heterogeneity (bank-municipality fixed effects, α_{bm}).[20] We are going to use this specification to analyze the effects on the stocks of deposits and cash inventory (y_{bmt}). Due to the presence of zeros (especially of cash inventories after the robberies), we apply the inverse hyperbolic sine transformation to the original variable.[21] To in-

[20]Standard errors are clustered either at the bank-municipality or at the municipality level.

[21]In the Online Appendix, we also consider the log of the original variable plus one to deal with zeros.

vestigate the existence of pre-trends and to analyze the dynamics of the effects, we also employ a dynamic specification of Equation 1 using leads and lags of the variable $PostRobBank_{bmt}$. In the Online Appendix, we study aggregate effects on cash availability at the municipality level and, as our treatment is staggered, we provide robustness checks to the considerations summarized in Roth et al. (2022)

To study how the interruption of in-person services due to branch explosions affects the adoption of Pix and other payment technologies at the municipality level, we estimate the following specification using data at the municipality-week level:

$$y_{mt} = \alpha_m + \alpha_t + \delta Post\_Rob_{mt} + \beta_t \times 3G\_Cov_m + \epsilon_{mt} \qquad (2)$$

where y_{mt} is a measure of Pix utilization (or other payment methods) in municipality m and week t, $Post\_Rob_{mt}$ is a dummy variable that takes value 1 after the municipality m experiences a branch explosion, α_t is a vector of week fixed effects, and α_m is a vector of municipality fixed effects. To control for heterogeneous trends in adoption related to the quality of the local internet infrastructure, we include the interaction between week fixed effects and $3G\_Cov_m$. We cluster standard errors at the municipality level and weight the regression by CEM weights. Our coefficient of interest is δ, which gives us the impact of unexpectedly losing a physical branch on payment technology adoption in a window of six months (twenty-six weeks). We focus on short-distance, intra-municipality Pix transactions, as these were more likely to be carried out by cash before the loss of the branch.

In some exercises, we investigate whether results depend on the availability of other local branches by interacting $Post\_Rob_{mt}$ with the number of branches in the municipality. We explore the fact that we can identify if Pix users are firms or individuals to analyze if adoption is heterogeneous across these types of agents. For technologies that were available before Pix, we assess whether the impact of robbery events in the pre-Pix period is different than in the post-Pix period. Any heterogeneous response would shed light on the comparative advantages of Pix in relation to those existing technologies. Finally, we also inspect whether there are pre-trends in adoption and the pace of the effects by estimating the following dynamic specification:

$$Pix_{mt} = \alpha_m + \alpha_t + \sum_{\tau=1}^{q} \delta_{-\tau} Rob_{m,-\tau} + \sum_{\tau=1}^{q} \delta_{\tau} Rob_{m,\tau} + \beta_t \times 3G\_Cov_m + \epsilon_{mt} \qquad (3)$$

where $Rob_{m,t-\tau}$ is a dummy variable that takes value 1 if municipality m had a branch destruction τ weeks after t, and $Rob_{m,t+\tau}$ is a dummy variable that takes value 1 if municipality m had a branch destruction τ weeks before t.

Besides the analysis of direct effects at the affected municipality, we also test for spillover effects for transactions that were unlikely to be carried out by cash in the first place and for institutions that operate in the treated municipality but are not directly affected by the shock either because they operate digitally or because their branch was not targeted. To investigate the former case, we estimate Equation 2 using as dependent variable Pix transactions in which the payer is in the affected municipality and the payee in another municipality (outflows), and vice-versa (inflows). For such inter-municipality long-distance transactions, cash transaction costs are significant, suggesting that they were likely settled by an alternative payment method before Pix. To investigate local market spillovers for unaffected institutions, we use a version of Equation 1 and Pix data at the municipality-week-institution level. The dependent variables are the number of Pix transactions and the number of users. With this exercise, we can check whether there is an increase in the participation of digital banks after the robberies. This analysis allows us to test if digital banks can penetrate more easily in markets where individuals get acquainted with and trust digital technologies, and as a result, no longer need to rely on the physical infrastructure of brick-and-mortar branches and ATMs.

3 Results

3.1 Branch Outcomes: Cash Inventory and Deposits

We start by analyzing the types of branch services that are disrupted by the robberies using data aggregated at the bank-municipality level. This dataset contains only branch-based financial institutions, notably large banks; in particular, the data do not contain information on the deposits of digital banks. We estimate econometric specification 1 and report results in Table 2. We also report the results of the estimation of a dynamic specification in Figure 3.

The results on branches' cash inventory are very sizable, representing a reduction of 97% in the six months following the robbery.[22] These adverse effects seem to spill over for other banks in the same locality, but such effects are much smaller and less precisely estimated. These effects on unaffected branches are likely to be a result of people using an alternative bank for cash withdrawals.[23] There are some statistically significant short-term changes in the stock of deposits at the branches that suffered these attacks, but their magnitude is much smaller.

Figure 3 also depicts a 6-month persistence of the effects on branches' cash holdings: even though they increase slightly over time, they remain disproportionally lower even after 6 months of the criminal attacks. Banks deciding to close affected branches could be an explanation for these persistent results. However, we observe an insignif-

[22]As the cash inventory of many robbed branches drops to zero, we apply the inverse hyperbolic sine transformation to the dependent variable. We follow Bellemare and Wichman (2020) and use the formula $\exp(\beta) - 1$ to obtain a "growth" estimate: -97%=$\exp(-3.547) - 1$.

[23]Alternatively, banks could react to the robbery of their local competitors by reducing the amount of cash in their branches due to security concerns. However, smaller effects in the presence of more alternative branches in the technology adoption exercise seem to favor the former hypothesis.

icant amount of branch closures in our data and, even though we do not have data on when the branches reopen, anecdotal evidence suggests that they reopen in less than six months. In the next section, we show that this persistence can be explained by the explosion event triggering the local population to persistently demand less cash as individuals and firms collectively moved to an equilibrium with higher usage of alternative digital payments.[24]

3.2 Impact on Pix Usage

To analyze what happens in terms of Pix usage after the bank robberies, we focus on three main outcomes: the number of transactions, the value of transactions, and the number of users. Moreover, we also study usage patterns by the type of users and transactions made. With such information, we are able to check if the adoption was driven by business or household users making or receiving a payment.

Table 3 shows estimates for Equation 2 and provides evidence that Pix usage in municipalities that were exposed to bank branch attacks is disproportionately higher when compared to similar places that did not experience these events. We focus on short-distance, intra-municipality transactions (payer and payee in the same municipality), as such transactions were more likely to be carried out by cash before the shock. The results point out that these localities have a 9.2% higher number of Pix transactions and that the total municipal value of Pix payments is 7.6% higher six months after the robbery.[25] This table also provides evidence that municipalities with a higher number of branches experience a lower increase in the new technology usage. This result provides some 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 such locations seems to use other branches to obtain cash. In Figure 4, we show that localities of robbed banks and the control group follow a similar trend before the attacks in terms of Pix usage; however, after the attacks, these two groups start to diverge, and this divergence persists even six months after the shock.

Next, we proceed to analyze if the effects on Pix usage are different among firms and households. We use the same econometric specification, but we change the dependent variable to the number of unique users by municipality. In Table 4, we show that both the number of households that use Pix to send money and the number of households that use Pix to receive money are disproportionately higher after the shocks. Interestingly, when we look at the effects on business users, our results show that only the number of firms that use Pix to receive payments increases; there is no effect on the number of firms that use Pix to make payments. One possible explanation is that firms

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

[25] As we use the inverse hyperbolic sine transformation of the dependent variable but the effects are much smaller than those on cash inventories, the formula $\exp(\beta) - 1$ yields very similar numbers.

accept cash as payment from households, and thus the shortage of cash leads to an increase in Pix usage as a replacement for cash transactions with individuals. However, businesses usually do not pay their suppliers with cash, so the shortage of cash would not affect directly businesses as payers. Figure 5 depicts the dynamic effects.

We then study the effects on inter-municipality Pix transactions, i.e., transactions between accounts of treated and untreated municipalities. Inflows (outflows) are those transactions in which a firm or individual receives (makes) a transfer from (to) a firm or individual that is located in a different municipality. We use the econometric specification described in Equation 2 and provide the results in Table 5. The first two columns show evidence that the number of Pix transactions flowing in and out of the affected municipalities increased after the robberies. Regarding the number of users, the coefficients are overall positive and statistically significant, being stronger for firms than for households. In general, these spillover coefficients are slightly smaller than direct effects, but they show that Pix usage also increases for long-distance transactions for which the costs of using cash were already high before the branch explosion.

The results in this section indicate that, after a sudden increase in cash handling costs, individuals increase the usage of the new instant payment technology, while businesses increase the usage of the new technology specifically as a way to receive payments from customers. Moreover, we provide evidence that households increase Pix usage to perform long-distance transactions, which are arguably less affected by the loss of the branch than short-distance transactions.

Our results are consistent with several factors posited in the literature that impede financial technology adoption. When the costs of dealing with cash spike, agents face a "constrained optimization problem" in which 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. That is, Pix is now a solution to an "unconstrained optimization problem." This fact is consistent with agents paying the fixed adoption costs (e.g., learning) when the branch was unavailable, and then, when the branch reopens, Pix is more competitive because these costs are now sunk. Another explanation is that, as individuals are collectively induced to adopt Pix, its appeal increases due to adoption complementarities (Alvarez et al., 2022; Crouzet et al., 2023; Higgins, 2022).

3.3 Pix Usage Spillovers for Unaffected Institutions

We now turn to the question of whether institutions that operate in an affected municipality but are not directly affected by the shock experience an increase in Pix usage. These institutions are either digital banks, that by definition do not have branches, or branch-based banks that have a branch in the municipality whose operation is not affected by the robbery. To do that, we use data for each institution offering Pix payment services. Instead of data at the municipality-week level, as in the previous section, we use data at the municipality-institution-week level. Thus, we can separate the effects on the treated municipalities into effects on the robbed institutions (direct effects) and unaffected institutions (spillover effects).

Tables 6, 7, 8 show the results for the number of Pix transactions, number of active Pix users, and value of Pix transactions, respectively. These results are based on a specification analogous to Equation 1 with weekly periodicity and using all Pix providers instead of only banks. Columns 1 and 2 of these tables present the effects on households, while columns 3 and 4 present results for firms. There are two sets of coefficients: (i) the post-robbery coefficients of robbed institutions (direct effects) and (ii) the post-robbery coefficients of unaffected institutions in municipalities that experience a robbery (spillover effects). We calculate them for different types of institutions: branch-based private banks, state-owned banks, digital institutions, and credit unions.

Overall, our results show positive coefficients, meaning an increase in Pix transactions, active users, and value after the shock for robbed and non-robbed institutions in treated municipalities. While the direct effects on robbed institutions provide evidence of increased transactions and active users after the event, we do not observe an expansion in the value of transactions in the same institutions, except for firms acting as payees.

As a Pix transaction is made through banks' apps or websites, and these channels are not affected by the robbery, we would not expect such spillovers if digital institutions lacked the ability to provide these services effectively or if barriers to their growth persisted. However, we observe significant spillover effects in Pix usage for digital institutions not only when an account holder is receiving a Pix transaction (payee), but also when an account holder is making a Pix transaction (payer). The group of digital institutions is the only one that has significantly positive spillover effects for all our measures of Pix usage. Moreover, these institutions are in general the ones that experience the largest spillovers.

The results on how Pix adoption spills over to other financial institutions shed light on the effects of bank branch disruptions on local financial competition, providing evidence that these disruptions can spur the participation of digital institutions by reducing barriers associated with high cash dependence. In the next section, we check if the increased use of electronic transactions in digital institutions produces side benefits to their participation in credit markets.

3.4 Impact on Credit

In this section, we analyze whether the shocks we study have any effect on credit variables. First, we employ the same specification as in Section 3.2 to analyze the effects of such events on the total credit at the municipality level. Second, we analyze the direct and spillover effects before and after the introduction of Pix to affected and unaffected institutions with different levels of digitization, using the same specification as in Section 3.3.

In Table 9, we provide estimates of the effects on loan origination at the municipality level. Our results point out that the number of borrowers and loan amounts to households do not change significantly after the shock. Analyzing credit to firms, we find similar results, except for the number of clients, which marginally increases during the period of time after the introduction of Pix. Our results differ from the findings in other papers, which analyze the effects of branch closings on credit supply in different contexts (Nguyen, 2019; Bonfim et al., 2021). These differences are possibly driven by the temporary nature of the shock and by Brazilian banks' high level of digitalization. For instance, Silva et al. (2023) show that more digitized banks dealt well with credit provision even when there was an interruption in the physical operations during the COVID pandemic.

However, these results hide an interesting heterogeneity between affected branch-based banks and digital institutions. We present these heterogeneity results in Figure 8 for household credit and Figure 9 for business credit. In both cases, the dependent variables are the number of clients with new loans and the total value of these loans. For the affected banks, we see a clear reduction in both the number of clients and the amount of household credit. This result indicates that, for traditional banks, in-person interactions with loan officers that take place at branches are important for the provision of household credit. Indeed, in Panel C of Table A1, we show that 51.6% of loans were granted inside branches in 2020. For unaffected institutions, results are mainly statistically insignificant, except for the strong positive and statistically significant coefficients of digital institutions. Moreover, coefficients for the post-Pix period are higher than for the pre-Pix period, suggesting that the post-pandemic digitalization trend and the availability of Pix may be beneficial for competition in credit markets. The results also suggest economies of scope between credit and payment services, especially because the increase in Pix usage documented previously may improve the information available for institutions for credit analysis.

For business credit, results are less clear. For affected private banks, there is an increase in the number of clients, but not in the loan amount. For affected public banks, coefficients are statistically insignificant. Among unaffected institutions, digital institutions again stand out as the main beneficiaries of cash shortages, but only in the post-Pix period. For unaffected institutions, the post-Pix period has stronger effects than the pre-Pix period as in the case of household credit.

Overall, the empirical evidence in this section suggests that branches of traditional banks are more important for household credit than for business credit. Moreover, the disruption of bank branches' operations affects local banking competition in favor of digital institutions, especially after the introduction of Pix. We hypothesize that once there is less local dependence on cash, and there is an appropriate electronic substitute such as Pix, individuals start using digital institutions as those have more comparative advantage in providing digital financial services (Core and De Marco, 2021; Silva et al., 2023). Moreover, due to the complementarities between payments and credit, individuals also start to borrow from those institutions.[26]

4 Robustness Checks and Effects on Other Outcomes

4.1 Stacked Difference-in-differences

Recent articles have shown that researchers need to be cautious about interpreting the results of two-way fixed effects models (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021; Chaisemartin and D'Haultfœuille, 2020). Aware of such issues, we stack the robbery events-specific data to calculate an average effect across all the events (Baker et al., 2022). We augment their stacked difference-in-differences approach using the coarsened exact matching technique as in our baseline specifications.

In Table A8, we replicate the results in Table 3, which uses the two-way fixed effects specification. The results presented in such a table are quantitatively similar to those in our baseline specification. 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 mediates these results.

4.2 Impact on Other Payment Methods

In this section, we extend our analysis to other payment methods. Specifically, we investigate the effects of robbery events on the use of credit cards, debit cards, TED transfers, and *boleto*. In order to investigate how the emergence of Pix changes the way people react to a decrease in access to cash, we divide the analysis into pre-Pix and post-Pix.

We present the results for the number and value of transactions in Figure 6 and for the number of clients in Figure 7. Pix usage experiences the largest increase among these methods. Debit card usage also increases after the robbery events, both in the pre- and post-Pix periods. Debit cards have relatively low costs and, as these products 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 and Pix (e.g., they cannot be used in person-to-person transactions), they are able to help individuals and firms weather the increase in cash access costs. Credit cards, on the other hand, have negative coefficients that are statistically significant after Pix. One potential explanation is that, as the number of Pix adopters increases after the shock, it becomes a more attractive payment method and thus crowds out credit cards.

[26]Nevertheless, part of this stronger post-Pix result might be driven by a post-pandemic digitalization trend that led to a transition to digital services and the growth of digital institutions. That is, in a counterfactual world where Pix was not introduced after November 2020, we would still observe stronger effects for digital institutions due to network effects and stronger and more trustworthy brands.

TED – the closest Pix substitute – is the payment method that is most affected by the arrival of Pix. Before Pix, agents increase the number of TED transactions. However, after the introduction of Pix, there is no longer an effect on TED usage, with coefficients even negative, but not statistically significant. Regarding *boleto* payments, which are not close substitutes to either cash or Pix, the effects are in general negative but not precisely estimated.

Overall, these results suggest that agents are using more Pix and debit cards to deal with the negative effect on cash provision, at the expense of credit cards and TED, which are more expensive payment methods.

4.3 Bank Robberies and Other Criminal Activity

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. As we argue in Section 2.3, these robberies are one-off events that are performed by non-local criminals, and therefore they are unlikely to be linked to changes in criminal activity locally.

We provide evidence for this claim by studying the effects on homicides. This is the type of crime for which we have better data because (i) the harmonization across municipalities is more straightforward, and (ii) the issue of underreporting is less severe. First, although we do not use the number of homicides in our matching procedure, the number of homicides per 1000 inhabitants is not statistically different between our treated and control municipalities for the time period included in our sample (Table 1). Second, in Figure 10, we provide a regression result with time and municipality fixed effects that show that robberies are neither preceded nor followed by changes in homicides.

For one state (Minas Gerais), we were able to collect relatively high-quality data on other types of robberies. In Table A10 of the Online Appendix, we show that other types of robberies are not affected by a branch explosion. These results bear out the hypothesis that such events are exogenous to local criminality conditions.

4.4 Bank Robberies and Real Effects

The loss of a branch is definitely 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. This information, although not ideal, is the best one we have to check short-term effects on the real economy. Table A11 of the Online Appendix shows that, at least according to these measures, the shocks do not seem to affect the local economy. These results, however, should be interpreted with cautiousness because hiring and firing decisions involve costs and reflect medium- and long-term expectations. Moreover, this data only reflects formal firms' decisions and there is a large incidence of informality in the country.

5 Conclusion

We document that the presence of physical branches and financial technology adoption have considerable linkages. We first confirm that the shock we study – the sudden and unexpected interruption of branch services – increases cash access costs as the robbed branches' cash inventory drops significantly. We then show that the use of digital technologies increases. After the robbery events, we document a persistent increase in the use of Pix, a new instant payment method in Brazil, indicating the existence of frictions that prevent adoption. For individuals, the increase in usage happens both when they are the payer or payee, while for firms, the positive effects occur only when they are the payee.

Moreover, we show that there are important spillover effects for other municipalities not affected by the robberies and for other non-robbed banks in municipalities affected by these crimes. Our results also show that Pix adoption after these branch disruptions increases in digital financial institutions and that such disruptions positively impact their credit participation, especially after Pix was introduced. These results shed some light on the role that new digital payment methods can play in increasing financial competition by boosting digital institutions' ability to compete with conventional banks in the payment and credit markets.

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Tables

Table 1: Original and Matched Sample

	With Robberies	Without Robberies	Diff. (p-value)
Panel A: Original sample			
3G Internet Coverage	42	43	0.86
3G Population Coverage	79	77	0.02
3G Households Coverage	79	77	0.02
Municipal Area (km)	967	677	0.01
Municipal Population	21,737	14,525	0.00
Municipal Households	6,349	4,292	0.00
Municipal GDP	302,715	200,677	0.00
Number of observations	450	3,317	
Panel B: Matched sample (CEM)			
3G Area Coverage	43	44	0.89
3G Population Coverage	78	78	1.00
3G Households Coverage	79	79	0.95
Municipal Area (km)	612	565	0.31
Municipal Population	16,393	15,215	0.18
Municipal Households	4,838	4,500	0.19
Municipal GDP	187,894	182,291	0.72
Number of observations	365	2,370	
Panel C: Variables not included in the CEM procedure			
Homicide rate (2018)	20.188	18.255	0.197
Number of branches (2017)	1.449	1.446	0.976
Credit per capita (2017)	3.805	4.454	0.057
Deposits per capita (2017)	3.173	3.476	0.131
Agriculture value added (2019)	41.353	37.701	0.225
Manufacturing value added (2019)	56.432	58.469	0.802
Services value added (2019)	126.376	120.821	0.590

Notes: Panel A compares baseline characteristics of the original sample, which is comprised of municipalities with fewer than 10 branches and service stations located in the states for which we have robbery data. Panel B compares the baseline characteristics of the matched sample using the Coarsened Exact Matching (CEM) procedure. The local characteristics (measured in 2019) used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table 2: Bank Robberies and branch Outcomes

	Total Deposits	Cash Holdings
	(1)	(2)
Post Robbery Bank	-0.025**	-3.547***
	(0.012)	(0.275)
Post Robbery Municipality	0.008	-0.201
	(0.008)	(0.126)
Bank X Municipality FE	Yes	Yes
Bank X Time FE	Yes	Yes
3G Internet Cov. X Time FE	Yes	Yes
N	155,587	155,587
R2	0.876	0.762

Notes: The table presents estimates of Equation 1. In all regressions, the post-robbery window has a length of six months. In column 1 (2), the dependent variable is the inverse hyperbolic sine transformation of the stock of deposits (cash holdings). The coefficient of *Post Robbery Bank* reflects effects on robbed banks, while the coefficient of *Post Robbery Municipality* reflects spillover effects for non-robbed banks that operate in a municipality that has a branch explosion. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table 3: Bank Robberies and Intra-Municipality Pix Usage

	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity			Value		
Post Robbery	0.093***	0.092***	0.269***	0.074**	0.076**	0.208***
	(0.031)	(0.030)	(0.046)	(0.036)	(0.033)	(0.066)
Post Robbery $\times$ # Branches			-0.065***			-0.049***
			(0.012)			(0.016)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Week x 3G Coverage FE	No	Yes	Yes	No	Yes	Yes
# Observations	225,708	225,708	225,708	225,708	225,708	225,708
# Municipalities	2,737	2,737	2,737	2,737	2,737	2,737
# Treated Municipalities	33	33	33	33	33	33
R2	0.9870	0.9894	0.9894	0.9361	0.9482	0.9482

Notes: The table presents estimates of Equation 2. In all regressions, the post-robbery window has a length of twenty-six weeks. In columns 1-3 (4-6), the dependent variable is the inverse hyperbolic sine transformation of the quantity (total 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. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table 4: Bank robberies and the number of Pix users in intra-municipality transfers

	(1)	(2)	(3)	(4)
	# Households		# Firms	
	Payer	Payee	Payer	Payee
Post Robbery	0.096***	0.094***	0.061	0.135***
	(0.029)	(0.029)	(0.041)	(0.039)
Municipality FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Week x 3G Coverage FE	Yes	Yes	Yes	Yes
# Observations	225,708	225,708	225,708	225,708
# Municipalities	2,737	2,737	2,737	2,737
# Affected Municipalities	33	33	33	33
R2	0.9900	0.9892	0.9718	0.9735

Notes: The table presents estimates of Equation 2. In all regressions, the post-robbery window has a length of twenty-six weeks. In column 1 (3), the dependent variable is the inverse hyperbolic sine transformation of the number of households (firms) that are payers in intra-municipality Pix 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. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table 5: Bank robberies and Pix usage spillovers (inter-municipality transfers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity		# Households		# Firms	
	Inflow	Outflow	Inflow	Outflow	Inflow	Outflow
Post Robbery	0.069**	0.070***	0.041*	0.053***	0.077**	0.072**
	(0.029)	(0.020)	(0.024)	(0.019)	(0.032)	(0.030)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Week x 3G Coverage FE	Yes	Yes	Yes	Yes	Yes	Yes
# Observations	225,708	225,708	225,708	225,708	225,708	225,708
# Municipalities	2,737	2,737	2,737	2,737	2,737	2,737
# Affected Munic.	33	33	33	33	33	33
R2	0.9903	0.9924	0.9932	0.9938	0.9751	0.9771

Notes: The table presents estimates of Equation 2. In all regressions, the post-robbery window has a length of twenty-six weeks. In all columns, the dependent variable is the inverse hyperbolic sine transformation of the original variable. The original variables are: in column 1, the number of Pix transactions in which the sender is in a different municipality; in column 2, the number of Pix transactions in which the recipient is in a different municipality; in column 3 (5), the number of individuals (firms) that receive Pix transfers from senders that are located in a different municipality; in column 4 (6), the number of individuals (firms) that make Pix transfers to recipients that are located in a different municipality. Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table 6: Bank robberies and the number of Pix intra-municipality transfers by bank type

	(1)	(2)	(3)	(4)
	Household		Firms	
	Payer	Payee	Payer	Payee
Post Robbery - treated banks (**direct effects**)				
Private Banks	0.410***	0.162**	0.199	0.313*
Branch-based	(0.095)	(0.075)	(0.138)	(0.185)
State-Owned	0.117*	0.106**	0.313***	0.474***
Banks	(0.062)	(0.044)	(0.087)	(0.066)
Post Robbery - non-treated banks in affected municipalities (**spillover effects**)				
Private Banks	0.096***	0.078***	0.164***	0.250**
Branch-based	(0.035)	(0.028)	(0.063)	(0.101)
State-Owned	0.099	0.146**	0.031	0.054
Banks	(0.063)	(0.057)	(0.065)	(0.100)
Credit Unions	0.056**	0.055**	0.002	0.088
	(0.027)	(0.022)	(0.047)	(0.084)
Digital Institutions	0.156***	0.152***	0.100***	0.152***
	(0.018)	(0.019)	(0.029)	(0.037)
Other types	0.055**	0.067***	0.102	0.076
	(0.021)	(0.022)	(0.074)	(0.083)
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
# Observations	11,650,010	11,650,010	5,048,314	5,048,314
# Municipalities	2,737	2,737	2,737	2,737
# Affected Municipalities	33	33	33	33
# Institutions	720	720	620	620
R2	0.9241	0.9267	0.8386	0.8391

Notes: In all regressions, the post-robbery window has a length of twenty-six weeks. We report coefficients of the interaction of the post-robbery dummy with dummies for institution types. In column 1 (3), the dependent variable is the inverse hyperbolic sine transformation of the number of intra-municipality Pix transactions in which a household (firm) is the payer. In column 2 (4), the dependent variable is the inverse hyperbolic sine transformation of the number of intra-municipality Pix transactions in which a household (firm) is the payee. Standard errors are clustered at the municipality-bank level. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table 7: Bank robberies and the number of Pix users in intra-municipality transfers by bank type

	(1)	(2)	(3)	(4)
	Households		Firms	
	Payer	Payee	Payer	Payee
Post Robbery - treated banks (**direct effects**)				
Private Banks	0.419***	0.230***	0.050	0.116
Branch-based	(0.055)	(0.079)	(0.065)	(0.089)
State-Owned	0.284***	0.231***	0.171***	0.387***
Banks	(0.059)	(0.045)	(0.038)	(0.042)
Post Robbery - non-treated banks in affected municipalities (**spillover effects**)				
Private Banks-	0.109***	0.098***	0.082**	0.087**
Branch-based	(0.026)	(0.025)	(0.032)	(0.038)
State-Owned	0.051	0.087***	0.021	0.018
Banks	(0.035)	(0.032)	(0.031)	(0.042)
Credit Unions	0.034**	0.037***	-0.007	-0.007
	(0.015)	(0.013)	(0.026)	(0.036)
Digital Institutions	0.104***	0.095***	0.038***	0.062***
	(0.010)	(0.010)	(0.014)	(0.015)
Other types	0.041***	0.042***	0.062*	0.045
	(0.011)	(0.011)	(0.035)	(0.033)
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
# Observations	11,650,010	11,650,010	5,048,314	5,048,314
# Municipalities	2,737	2,737	2,737	2,737
# Affected Municipalities	33	33	33	33
# Institutions	720	720	620	620
R2	0.9275	0.9290	0.8346	0.8550

Notes: In all regressions, the post-robbery window has a length of twenty-six weeks. We report coefficients of the interaction of the post-robbery dummy with dummies for institution types. In column 1 (3), the dependent variable is the inverse hyperbolic sine transformation of the number of households (firms) that are payers in intra-municipality Pix 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-bank level. We apply the Coarsened Exact Matching (CEM) procedure. As the matching is at the municipality level but the data is at the municipality-institution level, regressions are weighted by the Coarsened Exact Matching weights times the inverse of the number of institutions in that municipality x week. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table 8: Bank robberies and the value of Pix intra-municipality transfers by bank type

	(1)	(2)	(3)	(4)
	Households		Firms	
	Payer	Payee	Payer	Payee
Post Robbery - treated banks (**direct effects**)				
Private Banks	0.189	-0.137	0.476	0.878***
Branch-based	(0.179)	(0.123)	(0.394)	(0.329)
State-Owned	-0.136*	-0.141**	-0.141	-0.142
Banks	(0.078)	(0.069)	(0.187)	(0.175)
Post Robbery - non-treated banks in affected municipalities (**spillover effects**)				
Private Banks	0.039	0.010	0.315	0.267
Branch-based	(0.121)	(0.088)	(0.226)	(0.250)
State-Owned	0.170	0.193	0.156	0.138
Banks	(0.157)	(0.136)	(0.238)	(0.322)
Credit Unions	0.212**	0.280***	0.045	0.253
	(0.090)	(0.076)	(0.180)	(0.243)
Digital Institutions	0.207***	0.151***	0.258***	0.425***
	(0.049)	(0.050)	(0.097)	(0.098)
Other types	0.138**	0.155***	0.440	0.275
	(0.061)	(0.060)	(0.284)	(0.239)
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
# Observations	11,650,010	11,650,010	5,048,314	5,048,314
# Municipalities	2,737	2,737	2,737	2,737
# Affected Municipalities	33	33	33	33
# Institutions	720	720	620	620
R2	0.8223	0.8274	0.7327	0.7483

Notes: In all regressions, the post-robbery window has a length of twenty-six weeks. We report coefficients of the interaction of the post-robbery dummy with dummies for institution types. In column 1 (3), the dependent variable is the inverse hyperbolic sine transformation of the value of intra-municipality Pix transactions in which a household (firm) is the payer. In column 2 (4), the dependent variable is the inverse hyperbolic sine transformation of the number of intra-municipality Pix transactions in which a household (firm) is the payee. Standard errors are clustered at the municipality-bank level. We apply the Coarsened Exact Matching (CEM) procedure. As the matching is at the municipality level but the data is at the municipality-institution level, regressions are weighted by the Coarsened Exact Matching weights times the inverse of the number of institutions in that municipality x week. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table 9: Bank robberies and credit origination

	Households		Firms	
	Clients	Value	Clients	Value
Panel A: Pre-Pix				
Post Robbery	0.006	-0.004	0.008	0.028
	(0.014)	(0.017)	(0.011)	(0.031)
Observations	99,505	99,505	99,505	99,505
R-squared	0.990	0.974	0.971	0.857
Panel B: Post-Pix				
Post Robbery	-0.003	0.010	0.045***	0.034
	(0.0074)	(0.019)	(0.017)	(0.076)
Observations	70,825	70,825	70,825	70,825
R-squared	0.994	0.976	0.979	0.857
Municipality FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
3G Coverage X Time FE	Yes	Yes	Yes	Yes

Notes: In all regressions, the post-robbery window has a length of six months. We report coefficients of the interaction of the post-robbery dummy with dummies for institution types. In column 1 (3), the dependent variable is the inverse hyperbolic sine transformation of the number of households (firms) that receive a new loan in a given month. In column 2 (4), the dependent variable is the inverse hyperbolic sine transformation of the total value of new loans to households (firms). Standard errors are clustered at the municipality level. We apply the Coarsened Exact Matching (CEM) procedure. As the matching is at the municipality level but the data is at the municipality-institution level, regressions are weighted by the Coarsened Exact Matching weights times the inverse of the number of institutions in that municipality x week. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Figures

Figure 1: Examples of branches destroyed because of robberies

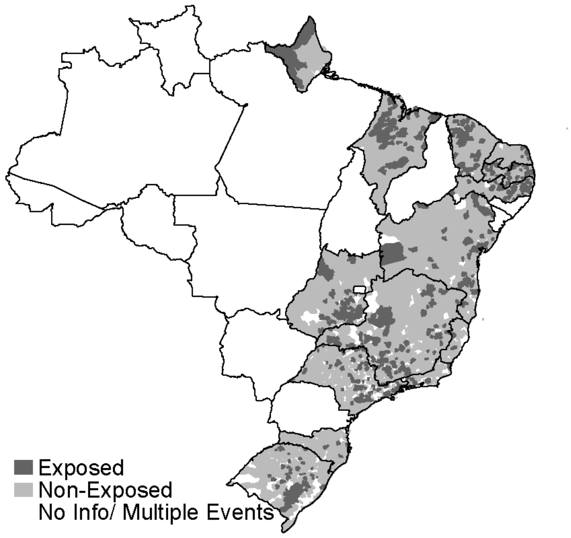
Source: https://atarde.com.br/bahia/ataques-a-bancos-na-bahia-aumentam-mais-de-400-no-periodo-de-janeiro-a-abril-1153220. Picture by: Olga Leiria / Ag. A TARDE

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

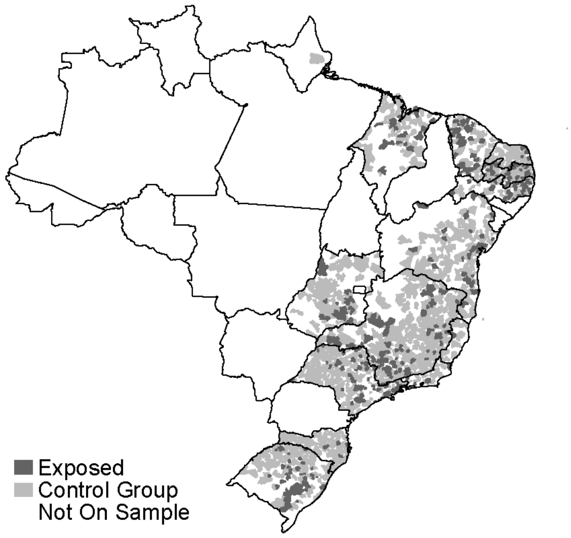
Source: https://g1.globo.com/mg/sul-de-minas/noticia/seis-agencias-bancarias-sao-alvos-de-explosao-e-roubo-em-tres-cidades-de-mg.ghtml. Picture by: Diego Batista/ Areado Notícias

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

Figure 2: Municipalities that suffered bank branch robberies (2018-2021)

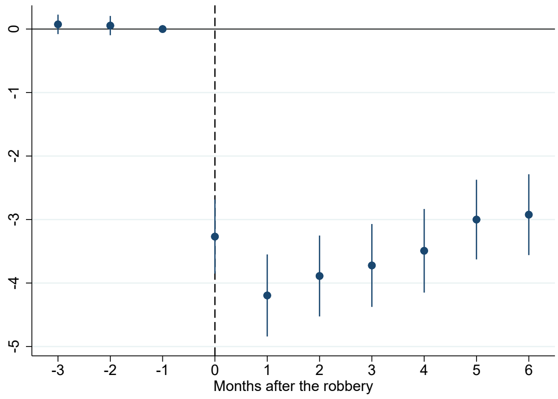


(**a**) Full Sample

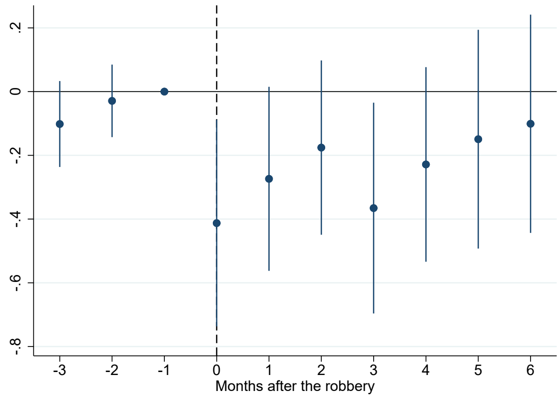


(**b**) CEM Matched Sample

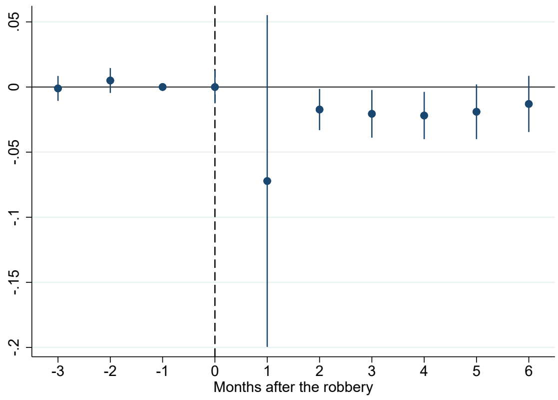
Figure 3: Bank Robbery and Branch Cash Inventory



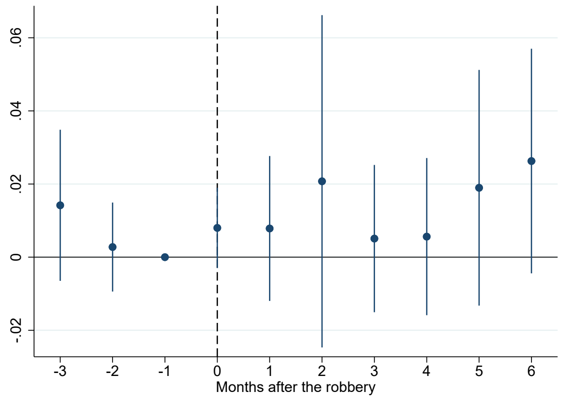
(a) Cash inventory: treated branches



(b) Cash inventory: local spillovers



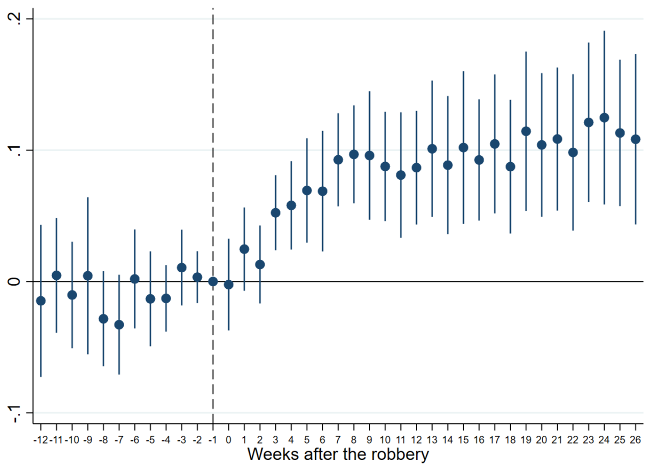
(c) Deposits: treated branches



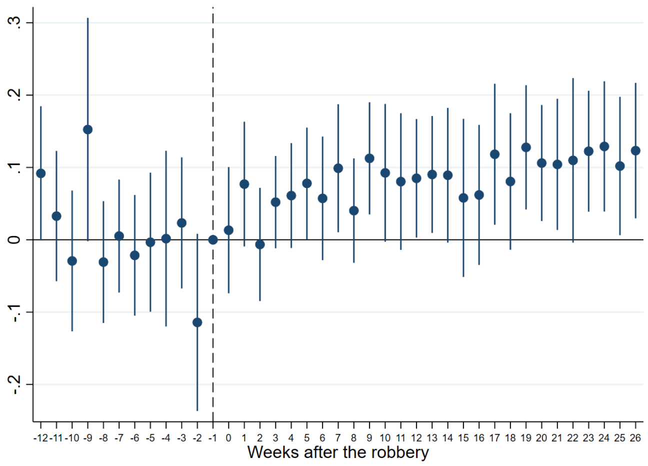
(d) Deposits: local spillovers

Notes: The figures report results from a dynamic version of Equation 1. We report 95% confidence intervals based on standard errors clustered at the municipality level. All specifications include bank-municipality and bank-time fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. Panels (a) and (c) display trajectories of robbed banks, while Panels (b) and (d) display trajectories of non-robbed banks that operate in a municipality that has a branch explosion. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Figure 4: Bank Robberies and Pix Adoption



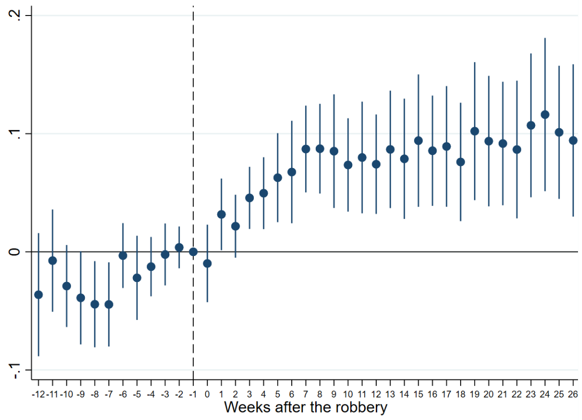
(a) Number of Pix Transactions



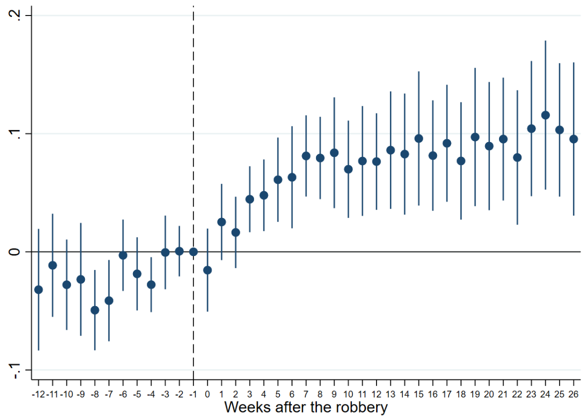
(b) Value of Pix Transactions

Notes: The figures report results from the estimation of Equation 3. 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. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

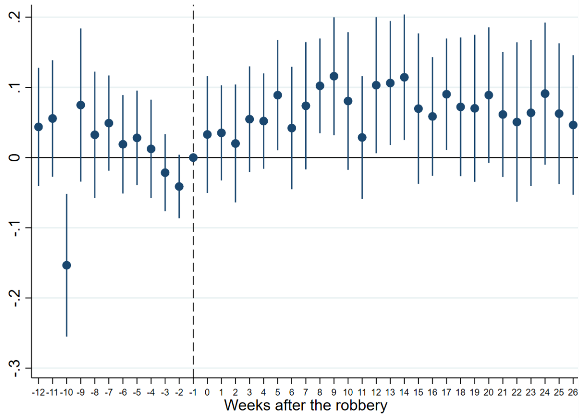
Figure 5: Bank Robberies and Number of Users by Transaction Type



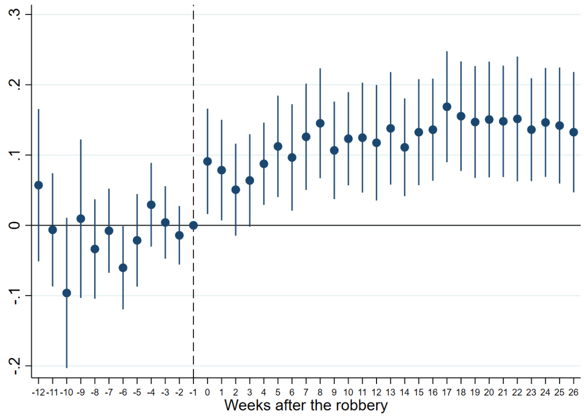
(**a**) Avg. Pix Non-Business Users - Payer



(**b**) Avg. Pix Non-Business Users - Payee



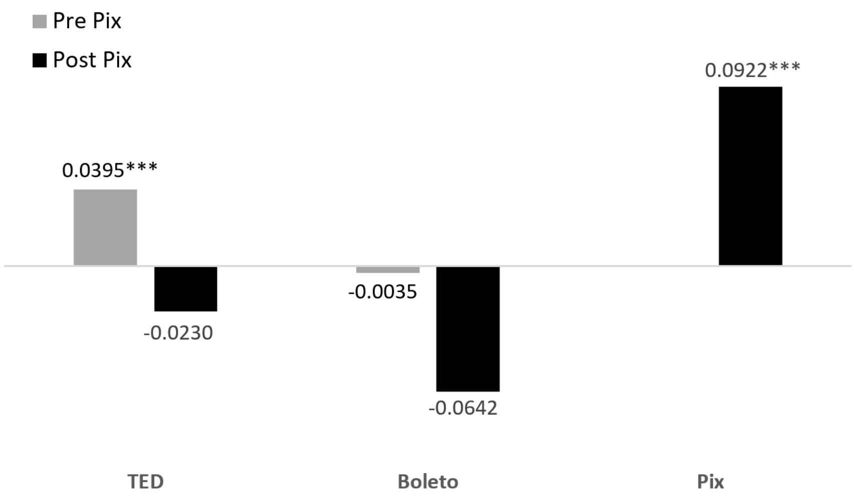
(**c**) Avg. Pix Business Users - Payer



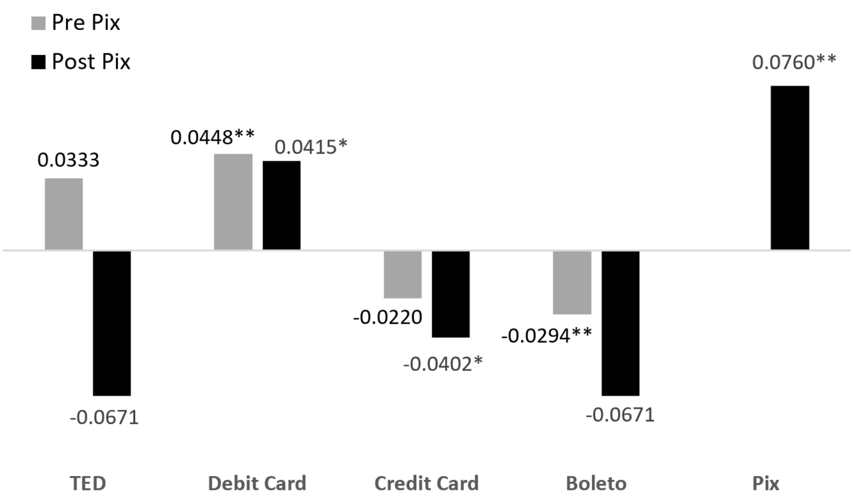
(**d**) Avg. Pix Business Users - Payee

Notes: The figures report results from the estimation of Equation 3. 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. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Figure 6: Payment Technologies - Number and Value of Transactions



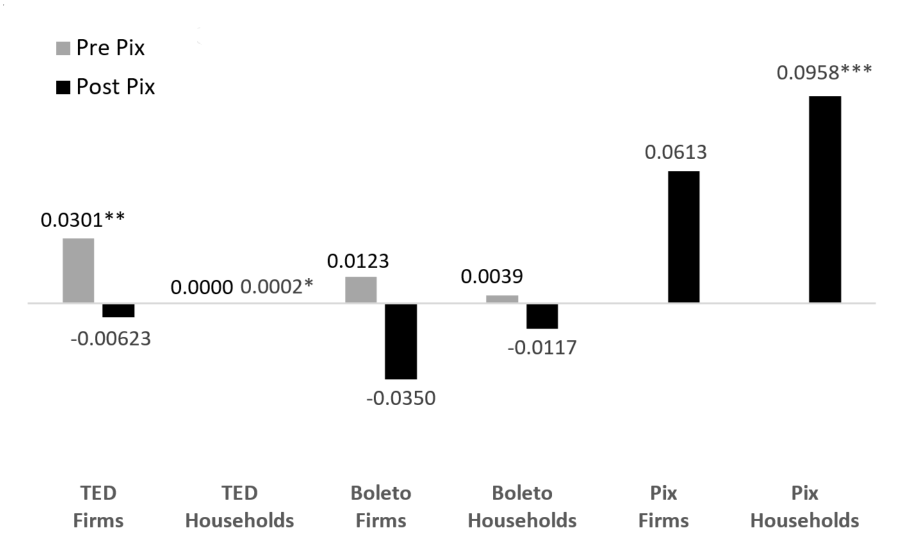
(**a**) Number of Transactions



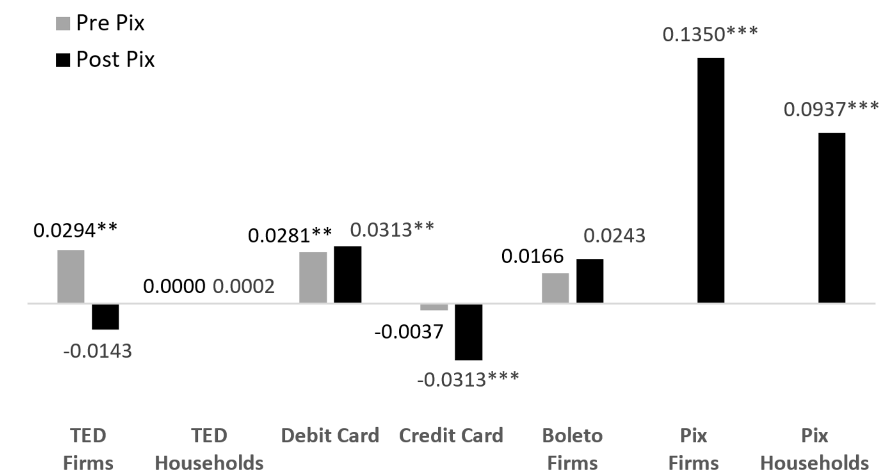
(**b**) Value of Transactions

Notes: The figures present estimates of Equation 2 for different payment technologies. We use two estimation windows: pre-pix (coefficients represented in grey bars) and post-pix (coefficients represented in black bars). For credit and debit cards, we only have data on the value of transactions. We cluster standard errors 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. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Figure 7: Payment Technologies - Number of Clients



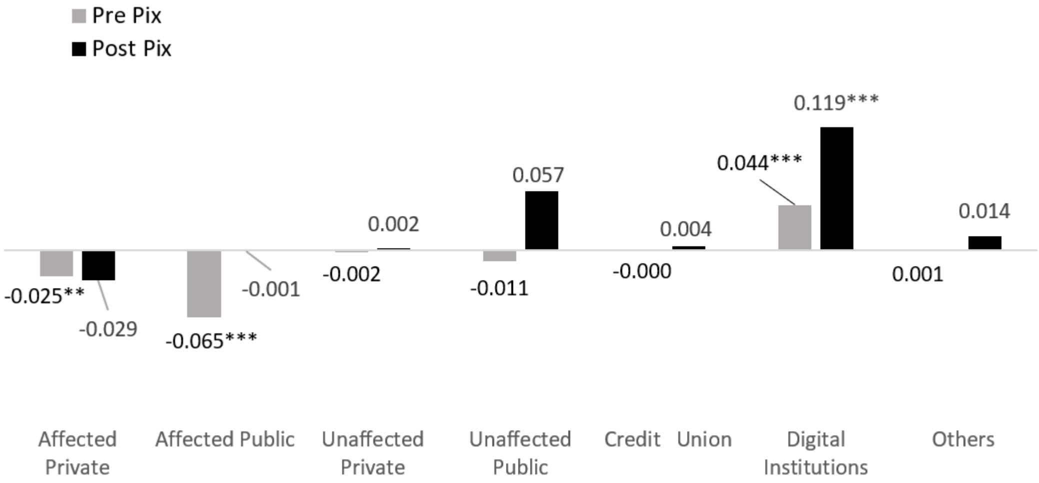
(a) Number of Payer Clients



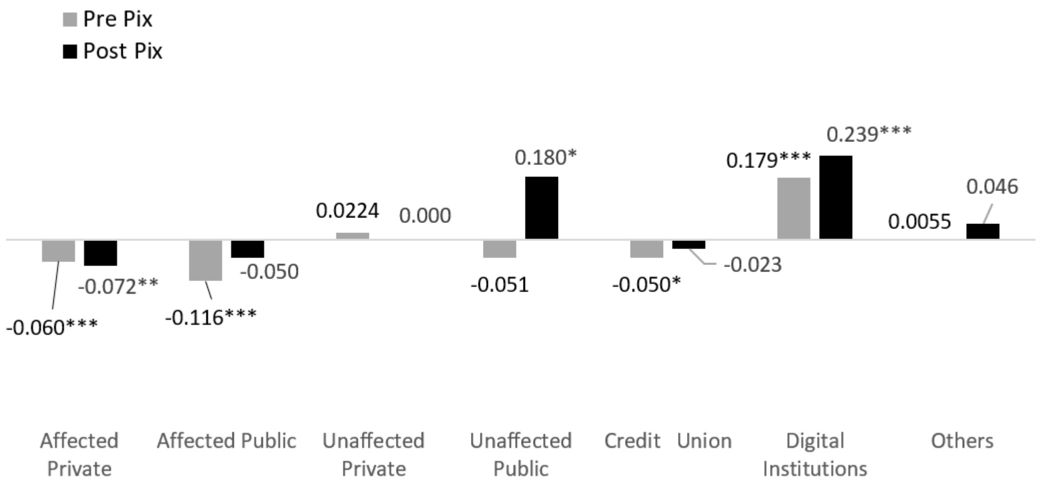
(b) Number of Payee Clients

Notes: The figures present estimates of Equation 2 for different payment technologies. We use two estimation windows: pre-pix (coefficients represented in grey bars) and post-pix (coefficients represented in black bars). For credit and debit cards, we only have data on the number of clients that make transfers (payees). We cluster standard errors 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. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Figure 8: Effects on Household Credit



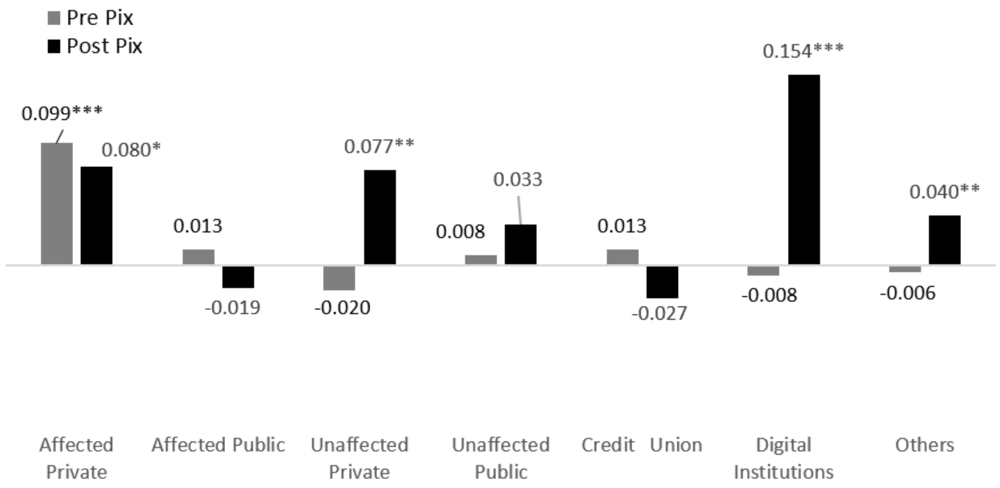
(a) Number of Credit Clients



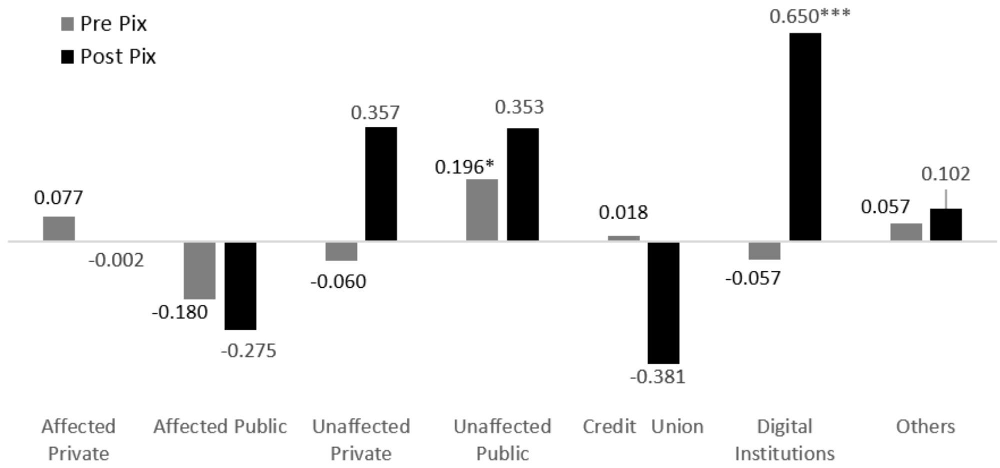
(b) Volume of Credit

Notes: The figures present estimates of Equation 1 for different credit variables. We include interactions of the post-robbery dummy with dummies for institution types. We use two estimation windows: pre-pix (coefficients represented in grey bars) and post-pix (coefficients represented in black bars). We cluster standard errors at the municipality level. Regressions include municipality-institution fixed effects, institution-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. We apply the Coarsened Exact Matching (CEM) procedure. As the matching is at the municipality level but the data is at the municipality-institution level, regressions are weighted by the Coarsened Exact Matching weights times the inverse of the number of institutions in that municipality x week. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Figure 9: Effects on Credit to Firms



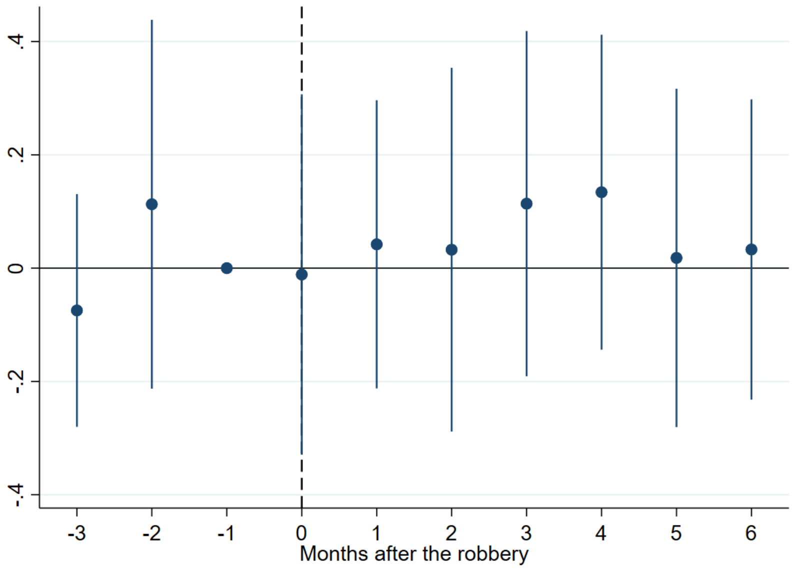
(**a**) Number of Credit Clients



(**b**) Volume of Credit

Notes: The figures present estimates of Equation 1 for different credit variables. We include interactions of the post-robbery dummy with dummies for institution types. We use two estimation windows: pre-pix (coefficients represented in grey bars) and post-pix (coefficients represented in black bars). We cluster standard errors at the municipality level. Regressions include municipality-institution fixed effects, institution-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. We apply the Coarsened Exact Matching (CEM) procedure. As the matching is at the municipality level but the data is at the municipality-institution level, regressions are weighted by the Coarsened Exact Matching weights times the inverse of the number of institutions in that municipality x week. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Figure 10: Effects of robberies on homicides



Notes: We report 95% confidence intervals are based on standard errors clustered at the municipality level. The regression includes municipality and time fixed effects. Due to a large number of zeros, we use as the dependent variable the inverse hyperbolic sine transformation of the number of homicides. We apply the Coarsened Exact Matching (CEM) procedure. The local baseline characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Online appendix to *Banks' Physical Footprint and Financial Technology Adoption*

Contents

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 Characteristics and importance of the main payment methods

Table A2: Characteristics of selected means to make transfers in Brazil

	Clearing	Type of transaction				Fees - individual		Fees - firm	
	time	P2P	B2P	P2B	B2B	S	R	S	R
Boleto	Up to 3 days	-	-	Yes	Yes	-	-	No	Maybe
TED	Minutes	Yes	Yes	Yes	Yes	Maybe	No	No	Maybe
Pix	Instant	Yes	Yes	Yes	Yes	No	No	Maybe	Maybe
Check	2 days	Yes	Yes	Yes	Yes	Maybe	No	Maybe	No
Debit card	1 day	-	-	Yes	Yes	No	-	No	Yes
Credit card	>2 days	-	-	Yes	Yes	Maybe	-	Maybe	Yes
Prepaid card	1 day	-	-	Yes	Yes	No	-	No	Yes

Note: P2P: person-to-person; P2B: person-to-business; B2B: business-to-business; B2P: business-to-person; S: sender of the funds; R: recipient of the funds.

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 shops that provide services on behalf of banks). As cash transactions are not recorded, we provide data on cash withdrawals. Direct debt refers to the automatic payment of recurrent (mostly utility) bills. Pix was launched in November 2020. Source: Brazilian Central Bank.

A1.3 Pix transactions by participant types

Table A4: 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.

Table A5: 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.

A1.4 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 segments: *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.

Report *Branching out: can banks move from city centers to digital ecosystems?*: The Economist Intelligence Unit, access: https://impact.economist.com/perspectives/sites/default/files/eiuglobalbankingreport2021_.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.

Number of POS terminals across countries: Bank for International Settlements, Payments and financial market infrastructures, Retail payment services and instruments. Access: https://stats.bis.org/statx/toc/CPMI.html.

A2 Robustness

A2.1 Municipality-level results using branch-level data

Table A6: Cash inventory: different weights and transformations

	(1)	(2)	(3)	(4)	(5)	(6)
	asinh(cash inventory)			ln(1+cash inventory)		
Panel A: Unweighted						
Post Robbery	-1.87***	-1.88***	-1.87***	-1.80***	-1.80***	-1.80***
	(0.24)	(0.24)	(0.24)	(0.23)	(0.23)	(0.22)
Observations	134,295	134,295	134,295	134,295	134,295	134,295
R2	0.66	0.67	0.67	0.67	0.67	0.67
Panel B: Unweighted, only positive CEM weights						
Post Robbery	-2.07***	-2.08***	-2.07***	-1.99***	-1.99***	-1.99***
	(0.28)	(0.28)	(0.28)	(0.27)	(0.27)	(0.27)
Observations	88,005	88,005	88,005	88,005	88,005	88,005
R2	0.64	0.65	0.65	0.64	0.65	0.65
Panel C: Weighted by CEM weights						
Post Robbery	-2.00***	-2.04***	-2.03***	-1.92***	-1.96***	-1.95***
	(0.29)	(0.29)	(0.29)	(0.27)	(0.27)	(0.27)
Observations	88,005	88,005	88,005	88,005	88,005	88,005
R2	0.69	0.69	0.69	0.69	0.69	0.70
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
3G Coverage X Time FE	No	No	Yes	No	No	Yes

Notes: In all regressions, the post-robbery window has a length of six months. In columns 1-3, the dependent variable is the inverse hyperbolic sine transformation of the aggregate cash inventory stored in branches of a given municipality, while in columns 4-6 the dependent variable is the natural logarithmic of one plus the aggregate cash inventory stored in branches of a given municipality. The sample is comprised of municipalities that had bank branches during the sample period. Standard errors are clustered at the municipality level. In Panel A, we provide results of OLS regressions using the entire sample; in Panel B, we provide results of OLS regressions using the sample of municipalities with positive Coarsened Exact Matching (CEM) weights; in Panel C, we apply the CEM procedure. The local characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

Table A7: Deposits

	(1)	(2)	(3)	(4)	(5)	(6)
	asinh(y)			ln(1+y)		
Post Robbery	-0.23*	-0.30*	-0.32*	-0.22*	-0.29*	-0.30*
	(0.13)	(0.16)	(0.16)	(0.12)	(0.16)	(0.16)
Observations	134,295	88,005	88,005	134,295	88,005	88,005
R2	0.62	0.60	0.63	0.62	0.60	0.63
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
3G Coverage X Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Restriction CEM weights > 0	No	Yes	Yes	No	Yes	Yes
CEM weights	No	No	Yes	No	No	Yes

Notes: In all regressions, the post-robbery window has a length of six months. The sample is comprised of municipalities that had bank branches during the sample period and the variable of interest is the total of deposits of branches in the municipality, that is, deposits in digital institutions or traditional banks that do have branches in the municipality are not accounted for. In columns 1-3, the dependent variable is the inverse hyperbolic sine transformation of the original variable, while in columns 4-6 the dependent variable is the natural logarithmic of the original variable plus one. Standard errors are clustered at the municipality level. In columns 1 and 4, we use the entire sample; in columns 3 and 6, we apply the Coarsened Exact Matching (CEM) procedure. The local characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP. In columns 2 and 5, we report an unweighted regression for the sample of municipalities with positive CEM weights.

A2.2 Municipality-level results using stacked difference-in-differences

Table A8: Bank robberies and pix usage: stacked difference-in-differences

	(1)	(2)	(3)	(4)	(5)	(6)
	Log(quantity)			Log(value)		
Post Robbery	0.107***	0.115***	0.263***	0.095***	0.105***	0.221***
	(0.028)	(0.029)	(0.054)	(0.032)	(0.032)	(0.071)
Post Robbery× # Branches			-0.057***			-0.044**
			(0.014)			(0.019)
Municipality X Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Week X Cohort FE	Yes	No	No	Yes	No	No
Week x 3G Cov. X Cohort FE	No	Yes	Yes	No	Yes	Yes
# Observations	71,660	71,660	71,660	71,660	71,660	71,660
# Municipalities	1,292	1,292	1,292	1,292	1,292	1,292
# Affected Municipalities	34	34	34	34	34	34
R2	0.9898	0.9900	0.9900	0.9381	0.9392	0.9392

Notes: In all regressions, the post-robbery window has a length of six months. In columns 1-3 (4-6), the dependent variable is the natural logarithm of the quantity (total 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. The local characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.

A3 Other outcomes

A3.1 The predictability of robberies

Table A9: Predictors of bank robberies

	(1)	(2)	(3)
	Bank Robbery		
3G Internet Area Coverage	-0.004	-0.002	0.002
	(0.008)	(0.011)	(0.012)
3G Internet Population Coverage	0.011	-0.008	-0.000
	(0.007)	(0.011)	(0.012)
Area	0.015*	0.025	0.012
	(0.008)	(0.025)	(0.019)
Population	0.040	0.111	-0.012
	(0.062)	(0.121)	(0.096)
Households	-0.003	0.038	0.034
	(0.063)	(0.126)	(0.098)
Municipal GDP	0.002	-0.013	-0.020
	(0.009)	(0.038)	(0.024)
Observations	3767	2735	2735
R-squared	0.020	0.055	0.002
Sample	All	CEM	CEM
CEM Weights	No	No	Yes

Notes: Linear probability model. Standard errors clustered at the state level. All independent variables on these regressions are standardized at the municipal level.

A3.2 Homicides and robberies

Table A10: Homicides and robberies

	(1)	(2)	(3)	(4)	(5)	(6)
	asinh(y)			ln(1+y)		
Panel A: Homicides						
Post Robbery	-0.01	-0.01	-0.01	-0.02	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Observations	155,322	130,344	130,344	155,322	130,344	130,344
R-squared	0.41	0.32	0.42	0.41	0.32	0.42
Panel B: Robberies, state of Minas Gerais						
Post Robbery	-0.00	0.01	0.02	-0.00	0.01	0.03
	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Observations	43,238	24,052	24,052	43,238	24,052	24,052
R-squared	0.58	0.28	0.34	0.57	0.28	0.34
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Restriction CEM weights > 0	No	Yes	Yes	No	yes	yes
CEM weights	No	No	Yes	No	No	Yes

Notes: Panel A uses homicide data at the municipality-month level from the *Sistema Nacional de Informações de Segurança Pública* (SINESP) from the Ministry of Justice and Public Security (access). The sample is comprised of municipalities located in states that provide homicide data for their municipalities in all the months between January 2018 and June 2022. Panel B uses robbery data at the municipality-month level for the state of Minas Gerais (MG). The data come from the Department of Public Security of the state (access). In all regressions, the post-robbery window has a length of six months. In columns 1-3, the dependent variable is the inverse hyperbolic sine transformation of the original variable, while in columns 4-6 the dependent variable is the natural logarithmic of the original variable plus one. Standard errors are clustered at the municipality level. In columns 1 and 4, we use the entire sample; in columns 3 and 6, we apply the Coarsened Exact Matching (CEM) procedure. The local characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP. In columns 2 and 5, we report an unweighted regression for the sample of municipalities with positive CEM weights.

A3.3 Real effects: labor outcomes

Table A11: Hirings and firings

	(1)	(2)	(3)	(4)
	Firings		Hirings	
Panel A: All sectors				
Post Robbery	-0.01	0.01	0.00	-0.00
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	183,822	183,822	183,822	183,822
R-squared	0.85	0.85	0.83	0.87
Panel B: Retail and restaurants firms				
Post Robbery	0.01	0.02	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Observations	183,822	183,822	183,822	183,822
R-squared	0.84	0.81	0.86	0.83
Firm size	All	Small	All	Small
Municipality FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
CEM	Yes	Yes	Yes	Yes

Notes: 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 (access). The labor data range from 2017 to 2021 (the last year available at the moment of the extraction). In all regressions, the post-robbery window has a length of six months and the dependent variable is the inverse hyperbolic sine transformation of the original variable. In columns 1 and 3, we include data from firms of all sizes, while in columns 2 and 4, we restrict the data to small firms, which we define as firms with less than 20 employees. Standard errors are clustered at the municipality level and we apply the Coarsened Exact Matching (CEM) procedure. The local characteristics used to perform the matching are the share of the area (km2) with 3G coverage, the share of the population with 3G access, the share of households with 3G access, area (km2), population, number of households, and GDP.