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Abstract*

We investigate how the presence of physical bank branches moderates financial technology diffusion. Our identification strategy uses services suspensions caused by criminal groups that perform hit-and-run raids exploding branch facilities and rendering them inoperable for months. We show that the shock depletes the cash inventory of branches, but the stock of credit and deposits remain unaffected. We then document that customers increase their usage of noncash payments after the events. We investigate a new instant payment technology called Pix that was a remarkable success in terms of adoption. After robbery events, the number and value of Pix intra-municipality transactions increase, as well as the number of users. We also find Pix usage spillover effects that go beyond cash substitution. First, the number of Pix transactions and users also increases when either the payer or the payee is in an unaffected municipality. Second, we show that there are local spillovers to digital institutions, indicating that cash dependence can be an impediment to their expansion. Our results shed light on the determinants of technology adoption and the consequences of the recent transition in the banking industry from a physical branch-based model to an increasing reliance on digital services.

JEL classifications: E42, E51, G20, O33
Keywords: Banking, Technology adoption, Payment methods

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1 Introduction

In the last decade, both developed and developing economies have witnessed a proliferation of new financial technologies and products and the entry of new firms in the financial sector. At the same time, 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 be a barrier to the penetration of alternative technologies (Alvarez et al., 2022; Crouzet et al., 2022; Higgins, 2020). Moreover, learning costs, lack of trust, organizational constraints, habit formation, and informational barriers can also hinder the adoption of new methods (e.g., Bachas et al., 2018; 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.

We explore the consequences of temporary, unexpected and exogenous branch closures, which disrupt in-person services, and, among other consequences, 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 a criminal activity that leaves branches inoperable for months. We show that such events induce the adoption of digital payment technologies, especially among individuals, and we document important spillovers to financial institutions that do not rely on a network of physical branches.

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

[1]The number of branches in Brazil decreased from 22,547 in 2016 to 17,644 in 2021 (Brazilian Central Bank); 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). According to the study *Branching out: can banks move from city centers to digital ecosystems?*, by The Economist Intelligence Unit, in 2021, 65% of banking executives believed the branch-based model will disappear within 5 years; in 2018, this number was 35%.

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, in the last decade, Brazil has experienced an increase in a new form of criminal activity that leads to a halt in the provision of in-person services offered by bank branches. Organized crime groups target branches, mostly in small- and medium-sized cities, through "hit-and-run" raids, using 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 financial services for a couple of months. Anecdotal evidence 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 particular, the costs of handling cash increase sharply, reducing its appeal as a means of payment.

This type of bank heist requires skilled personnel, meticulous training and planning, and an expensive apparatus. Therefore, the attacks are carried out by non-local organized groups and are not necessarily 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 high-frequency weekly and monthly data with a large set of covariates, we implement an event-study difference-in-differences empirical strategy around these criminal events using branches in similar 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 control branches, treated branches have virtually no cash right after an attack (-97%) and remain with a lower cash inventory for at least six months. We provide evidence that there are some minor short-lived spillover effects on cash inventories at 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 do not significantly affect the stock of lending or 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.[3] Next, we investigate whether branch explosions and local criminal activity are connected. We show that the shocks are neither followed nor preceded by an increase in homicides, supporting the hypothesis that such events are uncorrelated with trends in local crime.

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 Brazilian Central Bank. 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 connection to the internet. Before Pix, alternative options were costlier, not instant, or less user-friendly. Pix adoption was a remarkable success: between its

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

[3]Morales-Acevedo and Ongena (2020) show that bank robberies, especially the ones that occur during business hours and in which criminals use firearms, can affect the behavior of loan officers, at least in the short run. The robberies we study have different characteristics, which might explain the lack of strong results on credit.

launch and December 2021 (a 13-month period), 96 million individuals (54% of the adult population) have 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 in areas with a high number of alternative branches to perform cash withdrawals. 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).

Next, 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 then 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, 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 to institutions that operate in the treated municipalities but do not have a branch that was attacked. We show that the number of Pix transactions and users of non-robbed private branch-based banks, digital banks, and fintech payment institutions increases after a bank robbery in the municipality. The increase in the number of Pix users is especially important for non-branch-based banks and fintech payment 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, greater local reliance on cash can reduce the competitiveness of digital institutions. The results show that once this reliance is reduced, digital institutions can expand, possibly enhancing competition in the local financial market.

Our paper ties into a 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 (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 distort 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., 2022; Higgins, 2020; 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. This is important as a strand of recent research documents the benefits that new payment technologies can bring to consumers and firms.[4] 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.

Finally, our results 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 a 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).[5] The results also point to digital institutions having better IT capabilities and being better

[4]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 (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).

[5]In a sample of 123 countries, the average share of assets held by the 5 largest banks was 80.4% in 2021 (World Bank Global Financial Development Database).

equipped to provide digital payment services (Core and De Marco, 2021; D'Andrea and Limodio, 2020; Kwan et al., 2021).

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 assets and 80.5% of total credit in 2016. Despite a reduction in recent years, the same measures remain large in 2021 (assets, 68.6%; credit, 63.7%).[6] 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 2, 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 closure of a branch can be very disruptive, increasing the costs to withdraw and deposit cash, and at the same time increasing costs to monitor balances and apply for loans.

[6] 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.

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 was a TED transfer, which is used by both firms and individuals. It takes from a few seconds to a few hours to clear and can be carried out 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 the 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 A1 in the Appendix describes the characteristics of the main means of carrying out transfers. Table 1 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 Brazilian Central Bank launched a new instant payment system called Pix.[7] 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 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 costly, less user-friendly, and not instant.[8]

Pix adoption was a great success among individuals and firms: as of April 2022, 117.5 million individuals (around 55% of the population) and 9 million firms (around 47% of active firms) have

[7]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)

[8]The average TED fee per transaction is around BRL 17 in October 2020 (around USD 3 using the exchange rate of October 31, 2020). Source: https://www.bcb.gov.br/estabilidadefinanceira/tarifas_dados.

registered to use the system.[9,10] In Table 3, we show 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.[11] 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 (Zetta, 2021). 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 4, 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 and GDP per capita; their economies rely more on the manufacturing and services industries, and their population is more educated and has better internet access. In terms of characteristics of the financial sector, municipalities with higher Pix usage per inhabitant have more deposits, branches, and service stations with ATMs; their branches have a higher cash inventory and competition for deposits is larger according to the Herfindahl–Hirschman Index.

2.3 Bank Robberies

In recent years, a new criminal activity has erupted in Brazil: bank robberies that try to 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 (see Figures A1 and A2 in the Appendix), which needs to be refurbished to be operable again. The actions are carried out by sophisticated organized criminal organizations that operate in large swaths of the country. The raids 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 (Reuters, 2019).

Our sample contains records of robberies in 15 states (out of 27) between 2018 and 2021. The information used in our sample comes from the state public safety secretariats and is complemented with additional information from local news agencies about the name of the robbed banks and if there is the use of explosives when this information was not provided by the state secretariats. The states in our sample account for 75% of municipalities (4,168 out of 5,570), 82.3% of branches, and 81.4% of national GDP in 2019. We have a total of 1,396 establishments exploded in 775 municipalities. The fact that the number of establishments exploded is larger than the number of

[9] According to the Ministry of Economy, 18.9 million firms were active in September 2021. Source: https://www.gov.br/governodigital/pt-br/mapa-de-empresas/boletins/mapa-de-empresas-boletim-do-3o-quadrimestre-de-2021.pdf. According to estimates of the Brazilian Institute of Geography and Statistics (IBGE), Brazil had a population of 213.3 million in 2021.

[10] Not all registered individuals use Pix frequently. In our analysis, we use information on weekly active users.

[11] Economides and Jeziorski (2017) document higher fee elasticity for small-value and short-distance transfers.

municipalities is due to groups targeting more than one establishment simultaneously during the same raid (118 raids targeted more than one establishment, accounting for 301 events), or the municipality being targeted in different raids during our sample period (184 municipalities were targeted on more than one occasion, totaling 314 events). We exclude the municipalities that had more than one raid event because these 184 municipalities being targeted more than once might be very different from the 591 municipalities just targeted once, and some unobservable factor could be driving these repeated robberies. The number of explosions has fallen over time: 575 in 2018, 184 in 2019; 114 in 2020; and in 94 in 2021.

In Table 6, we show that municipal economic characteristics do not seem to be predictors of such criminal events. However, in Table 7 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.

In Figure A3 in the Appendix, we show that robberies are neither preceded nor followed by changes in local criminal activity. We focus on homicides due to better data availability and quality. This result bears out the hypothesis that such events are exogenous to local conditions.

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. 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.

Bank branch information. The Central Bank of Brazil (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 Central Bank of Brazil, while Sitraf is operated by CIP (*Câmara Interbancária de Pagamentos*).[12] 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.[13] We aggregate these 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. We collect Pix weekly information at the municipality level and at the municipality-PSP level.[14] We classify PSPs into 5 types:

- *Branch-based private banks*: private commercial banks with more than 1,000 branches;
- *Digital commercial banks*: private commercial banks that rely mainly on digital services;
- *State-owned commercial banks*: banks controlled by the central or local governments;
- *Payment institutions*: non-depository institutions that only provide payment services, including transfer or withdrawal of funds held in payment accounts (issuer of electronic money);
- *Credit unions*: financial institutions that provide credit and financial services to their members, and operate on a local market;

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-PSP level, we consider intra-municipality transactions, and for each institution type, we aggregate the cases where their clients are either payer or payee. Furthermore, we build a balanced panel of municipality-PSP-week. In some regressions, we divide Pix transactions

[12]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.

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

[14]In fact, our data are 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 for data. More information regarding Pix PSPs can be found at https://www.bcb.gov.br/en/financialstability/pixparticipants

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.

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 information on coverage in 2020, the first year when the data are 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.[15]

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 absence of the treatment. Although ex ante heterogeneity does not necessarily invalidate the method and, in our setting, treated and non-treated municipalities do not seem to be very different in terms of economic magnitudes, we implement a Coarsened Exact Matching 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 7, 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 weighing, these differences disappear, and the control and treatment groups become very similar. 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.[16]

We start by analyzing branch-level outcomes. We check the effects on the stock of loans, deposits, and cash holdings. Our specification also allows us to shed some light on the spillover effects of such crimes on other bank branches. If the main result of the explosion of branches is a depletion in the availability of cash, the effects on technology adoption are likely due to this factor

[15] In Table 9, we show that effects are indeed smaller in places with more branches.

[16] All our results are very similar in the unweighted sample and available upon request.

instead of other consequences of the shock. 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 value 1 after the bank b experiences a branch explosion in municipality m, while $PostRobMun_{bmt}$ takes 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}).[17] We are going to use this specification to analyze the response of banks to the attacks in terms of lending, deposits, and cash inventory (y_{bmt}). To investigate 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 $PostRobBank_{bmt}$.

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

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

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 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 time 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.

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 those 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

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

those existing technologies. Finally, we also inspect whether there are pre-trends in adoption and the pace of the effects by estimating the following specification:

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

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 to transactions that were unlikely to be carried out by cash in the first place and to 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 intra-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 to unaffected payment service providers (PSP), we use a version of equation 1 and Pix data at the municipality-week-PSP 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 become 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 Cash Inventory and Other Branch Outcomes

We start by analyzing the types of branch services that are disrupted by the robbery using data aggregated at the bank-municipality level (equation 1). We provide results in Table 8. There are no significant short-term changes in the stock of deposits or lending at the branches that suffered these attacks. On the other hand, the results on cash inventory are very sizable, representing a reduction of 97.9% in the six months following the robbery. These adverse effects seem to spill over to 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.[18]

In Figure 2, we show the dynamics of the effects of robberies on branches' cash inventory in the

[18] 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.

months around these events.[19] The figure shows that banks that suffered the attacks have close to zero cash inventory in the month after the attack. The figure also depicts a 6-month persistence of such effects showing that banks' cash holdings increase slightly but 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 insignificant amount of branch closures in our data. Therefore, the persistence can be explained by banks operating with less cash inventory due to security concerns and/or because the explosion event triggered the local economy to move from an equilibrium with a high cash dependence to one with a smaller cash dependence and higher usage of alternative digital payments, which we document in the next section.

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 exploit 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 9 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 transactions (payer and payee in the same municipality), as such transactions are more likely to be carried out by cash. 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. 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 3, 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 10, 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 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

[19]Figures A4 and A5 in the Appendix show the same exercise for lending and deposits.

do not pay their suppliers with cash, so the shortage of cash would not directly affect businesses as payers.

These results indicate that, after a sudden increase in cash handling costs, consumers increase the usage of the new instant payment technology, while businesses increase the usage of the new technology as a way to receive payments from customers.

3.3 Impact on Other Payment Methods

In this section, we investigate how the emergence of Pix changes the way people react to a decrease in access to cash. To do that, we study how individuals increase the use of other payment methods after the robbery events before and after the introduction of Pix. Figure 4 shows the effects of such shocks on the use of credit cards, debit cards, TED and *Boleto* in the six months following the attacks.

Before Pix, agents increase the number of transactions using electronic transfers (TED) by 3.9% and the value of transactions using debit cards by 4.5%. However, these results change after the introduction of Pix: while the increase in the value of debit card transactions persists, there is no longer an effect on the number of TED transactions. This result suggests that individuals are not just using Pix to deal with the negative effect on cash provision, but also using Pix as an alternative to TED transactions, which are less user-friendly, more expensive and not instant.

3.4 Pix Usage Spillovers

We now turn to the question of whether the increase in Pix usage in the affected municipalities spurs Pix usage in other municipalities and in unaffected institutions that operate in municipalities that have a branch from a competitor bank attacked.

First, we use information from 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 11. 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 clients, the coefficients on columns 3 to 6 of Table 11 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 are higher.

We then use data for each Pix payment service provider (PSP) to check spillovers inside the affected municipality. Instead of data at the municipality-week level, as in the previous sections, we use data at the municipality-PSP-week level. Thus, we can separate the effects on affected municipalities into affected and unaffected institutions. The effects on non-robbed institutions in affected municipalities can be seen as a spillover inside the municipality.

Table 12 shows the results from that exercise, which is based on a specification analogous to equation 1 with weekly periodicity and using all Pix providers, instead of only banks. The dependent variables are the hyperbolic sine transformation of the number of Pix transactions of households (column 1), firms (column 2), and the total (column 3). 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, large state-owned banks, digital commercial banks, payment institutions, and credit unions.

Overall, Table 12 shows positive coefficients, meaning an increase in Pix usage after the shock by clients of both robbed and non-robbed institutions in treated municipalities, when compared to the control group. However, as expected, coefficients from affected institutions (the direct effects) are higher than those from unaffected institutions (the spillover), for the same institution type. Although these point estimates are higher, we cannot reject the hypothesis that the coefficients from affected and unaffected institutions are statistically equal.

Moreover, we observe statistically significant spillover effects for all institution types, when considering households (column 1). The highest spillover coefficients are from payment institutions and digital banks (13.8% and 18.6%, respectively). [20] This result suggests that Pix adoption by households is higher for more tech-savvy institutions. For firms, the spillover effects evidence is weaker, but still exists for branch-based private banks, payment institutions, and digital banks. For branch-based private banks, spillovers are more substantial for firms than for households.

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 local participation of digital banks and fintech payment institutions.

4 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 handling costs as the robbed branches' cash inventory drops significantly. We then show that the use of digital technologies increases but the stock of credit and deposits remains largely unaffected. After the robbery events, we document an increase in the number and value of Pix transactions and the number of users. For individuals, the increase in the number of users 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 to other municipalities not affected by the robberies and to other non-robbed banks in municipalities affected by these crimes. Our results also show that Pix adoption after these branch disruptions increase in digital financial institutions, shedding some light on the role that new digital payment methods can play in

[20] These two coefficients are statistically higher than the branch-based private banks coefficient.

increasing financial competition.

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Tables

Table 1: 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.

Table 2: 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.

Table 3: 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 4: 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)
Area with 3G/4G access	35	39	48	35	38	49
(% of geographical area, 2020)	(25)	(25)	(31)	(26)	(25)	(30)
Inhabitants with 3G/4G access	65	77	88	66	77	87
(% of population, 2020)	(19)	(16)	(13)	(19)	(17)	(14)
Literacy rate	81	85	90	77	86	92
(% of population age>10, 2010)	(10)	(8)	(6)	(8)	(7)	(4)
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 service stations	1.2	1.5	6.6	1.0	1.4	6.8
(2019)	(1.0)	(1.2)	(31.2)	(0.8)	(1.1)	(31.2)
Number of ATM stations	1.3	2.1	12.9	1.4	2.2	12.7
(2019)	(1.3)	(1.8)	(68.9)	(1.2)	(2.5)	(68.9)
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. Service stations have employees and provide fewer services than branches, especially payment services (unless carried out with an ATM). Service stations with an ATM do not necessarily have an employee present. We report means and, in parentheses, standard errors.

Table 5: Municipality characteristics by robbery incidence between 2018 and 2021

	Branches = 0		Branches > 0		
	Rob. = 0	Rob. > 0	Rob. = 0	Rob. = 1	Rob. > 1
Panel A: Socio-economic characteristics					
GDP	105	132	1363	3031	12052
(BRL millions, 2019)	(113)	(115)	(3818)	(8541)	(64359)
GDP per capita	19.7	15.2	29.7	31.2	31.9
(BRL thousands, 2019)	(21.0)	(19.9)	(29.7)	(31.3)	(33.3)
Share agriculture	21	16	16	15	11
(% of value added, 2019)	(15)	(12)	(14)	(15)	(12)
Share manufacturing	9	10	17	18	17
(% of value added, 2019)	(11)	(13)	(15)	(15)	(14)
Share services	28	28	42	41	46
(% of value added, 2019)	(9)	(8)	(13)	(13)	(14)
Population	7	11	42	72	259
(thousands, 2019)	(5)	(6)	(97)	(144)	(1101)
Area with 3G/4G access	40	41	43	46	51
(% of population, 2020)	(26)	(26)	(28)	(29)	(29)
Inhabitants with 3G/4G access	71	73	82	83	86
(% of population, 2020)	(19)	(18)	(16)	(16)	(16)
Literacy rate	84	77	89	88	89
(% of population age>10, 2010)	(9)	(9)	(7)	(8)	(8)
Panel B: Financial sector characteristics					
Branches' cash inventory	-	-	6.1	26.9	118.8
(BRL millions, 2019)	-	-	(20.1)	(245.6)	(947.1)
Total deposits	-	-	282	837	6439
(BRL millions, 2019)	-	-	(1224)	(5993)	(50990)
Deposits HHI	-	-	0.61	0.59	0.51
(2019, conditional on having a branch)	-	-	(0.31)	(0.32)	(0.29)
Number of branches	-	-	4.0	7.2	33.9
(2019)	-	-	(8.7)	(22.5)	(183.8)
Number of service stations	1.4	1.7	3.1	5.7	19.4
(2019)	(0.9)	(0.8)	(7.4)	(16.2)	(90.1)
Number of ATM stations	1.0	1.5	5.7	10.8	40.1
(2019)	(0.8)	(0.8)	(14.2)	(37.3)	(194.3)
Number of observations	1435	164	2115	278	176

Notes: We group municipalities by the number of branches and the number robberies (abbreviated as *Rob.*) between 2018 and 2021 that involve the explosion of the establishment (branch, service station with ATM or service station). The variables branches' cash inventory, deposits HHI and total deposits are computed conditional on the municipality having a branch. Service stations have employees and provide fewer services than branches, especially payment services (unless carried out with an ATM). Service stations with an ATM do not necessarily have an employee present. We report means and, in parentheses, standard errors.

Table 6: Predictors of bank robberies

	Bank Robbery		
	(1)	(2)	(3)
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)
N	3767	2735	2735
R2	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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 7: 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	0.025
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	

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 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: share of the area (km2) with 3G coverage, share of the population with 3G access, share of households with 3G access, area (km2), population, number of households, and GDP.

Table 8: Bank Robberies and Branch Outcomes

	(1)	(2)	(3)
Post Robbery Bank	-0.001	-0.025**	-3.547***
	(0.013)	(0.012)	(0.275)
Post Robbery Municipality	-0.016*	0.008	-0.201
	(0.009)	(0.008)	(0.126)
Bank X Municipality FE	Yes	Yes	Yes
Bank X Time FE	Yes	Yes	Yes
3G Internet Cov. X Time FE	Yes	Yes	Yes
N	155587	155587	155587
R2	0.939	0.876	0.762

Notes: The table presents estimates of equation 1. We consider a window of 3 months before the events and 6 months after them. The outcome variable is the inverse hyperbolic sine transformation of the variable of interest due to the presence of zeros. Regressions use the matched sample of Coarsened Exact Matching (CEM) procedure and are weighted by the CEM weights. Standard errors clustered at branch and municipality levels. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 9: Bank Robberies and Pix Usage

	Pix Quantity			Pix Volume		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Robbery Muni	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 Muni			-0.065***			-0.049***
$\times$ # Branches			(0.012)			(0.016)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	No	No	Yes	No	No
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
# Affected Municipalities	33	33	33	33	33	33
R2	0.9870	0.9894	0.9894	0.9361	0.9482	0.9482

Notes: i) Standard errors clustered at the municipality level. ii) Regressions use the matched sample of Coarsened Exact Matching procedure and are weighted by the Coarsened Exact Matching weights. iii) All variables are the inverse hyperbolic sine transformation of the original variable. iii) * p<0.10, ** p<0.05, *** p<0.01

Table 10: Bank Robberies and Pix Number of Clients

	# Households		# Firms	
	(1)	(2)	(3)	(4)
	Payer	Payee	Payer	Payee
Post Robbery Muni	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: i) Standard errors clustered at the municipality level. ii) Regressions use the matched sample of Coarsened Exact Matching procedure and are weighted by the Coarsened Exact Matching weights. iii) All variables are the Inverse Hyperbolic Sine Transformation of the original variable. iii) * p<0.10, ** p<0.05, *** p<0.01

Table 11: Bank Robberies and Pix Usage Spillovers

	Pix Quantity		# Households		# Firms	
	(1) Inflow (Payer)	(2) Outflow (Payee)	(3) Inflow (Payer)	(4) Outflow (Payee)	(5) Inflow (Payer)	(6) Outflow (Payee)
Post Robbery Muni	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: i) Standard errors clustered at the municipality level. ii) Regressions use the matched sample of Coarsened Exact Matching procedure and are weighted by the Coarsened Exact Matching weights. iii) All variables are the Inverse Hyperbolic Sine Transformation of the original variable. iii) * p<0.10, ** p<0.05, *** p<0.01

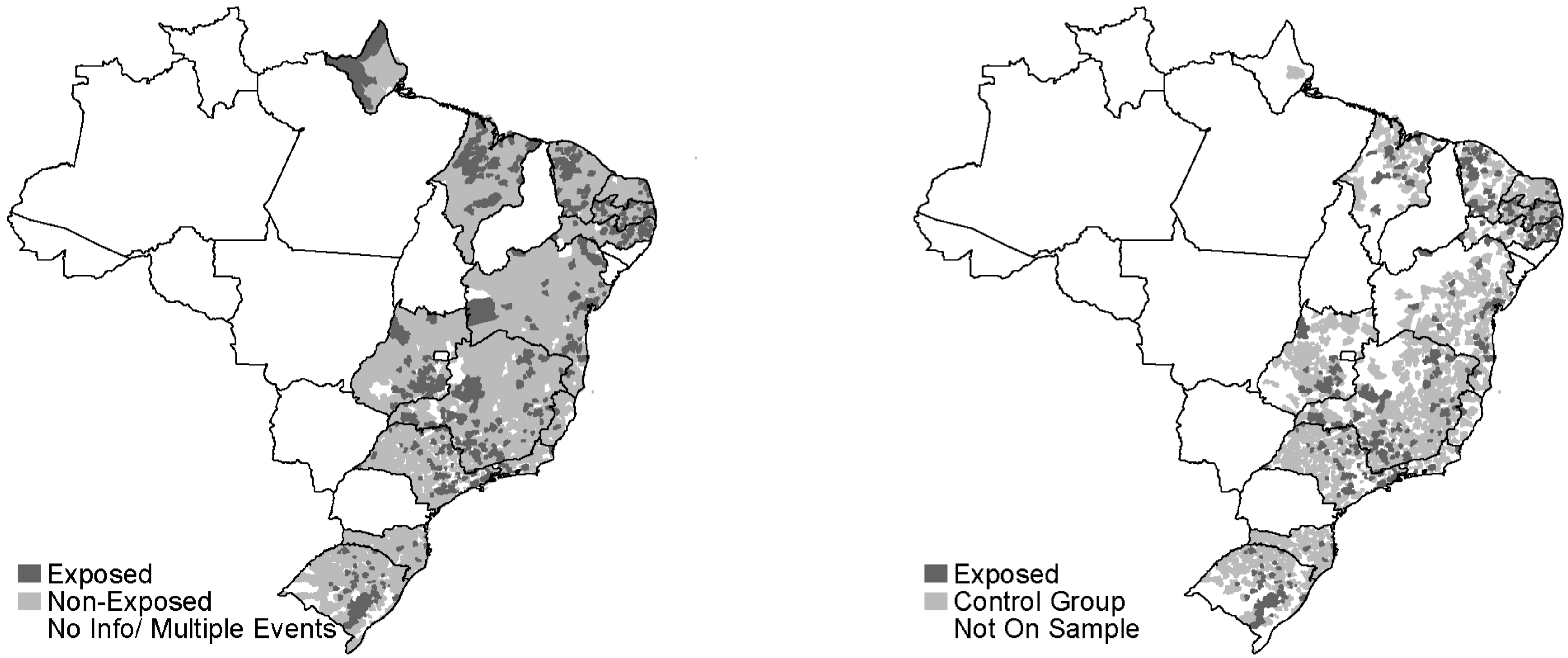
Table 12: Bank Robberies and Pix Usage Spillovers by Institution Type

	Pix Quantity		
	(1) Households	(2) Firms	(3) Total
Post Robbery - Affected Institutions in affected Municipalities			
(Direct Effects)			
Private Banks - Branch-based	0.244***	0.247*	0.239***
	(0.075)	(0.134)	(0.075)
Large State-Owned Banks	0.099**	0.320***	0.105**
	(0.048)	(0.061)	(0.046)
Post Robbery - Unaffected Institutions in affected Municipalities			
(Spillover Effects)			
Private Banks - Branch-based	0.081***	0.223**	0.064**
	(0.025)	(0.090)	(0.029)
Large State-Owned Banks	0.080*	0.133	0.072*
	(0.043)	(0.118)	(0.042)
Payments Institutions	0.138***	0.116**	0.135***
	(0.023)	(0.045)	(0.023)
Credit Unions	0.094***	0.074	0.100***
	(0.030)	(0.081)	(0.035)
Digital Commercial Banks	0.186***	0.204***	0.183***
	(0.045)	(0.072)	(0.044)
Muni x Institution FE	Yes	Yes	Yes
Week x 3G Coverage FE	Yes	Yes	Yes
Week x Institution FE	Yes	Yes	Yes
# Observations	11,625,418	4,924,427	12,597,656
# Municipalities	2,737	2,737	2,737
# Affected Municipalities	33	33	33
# Institutions	719	619	732
R2	0.9302	0.8552	0.9249

Notes: i) Standard errors clustered at the municipality level x institution level. ii) Regressions use the matched sample of Coarsened Exact Matching procedure and are weighted by the Coarsened Exact Matching weights times the inverse of the number of institutions on that municipality x week. iii) All variables are the Inverse Hyperbolic Sine Transformation of the original variable. iv) * p<0.10, ** p<0.05, *** p<0.01

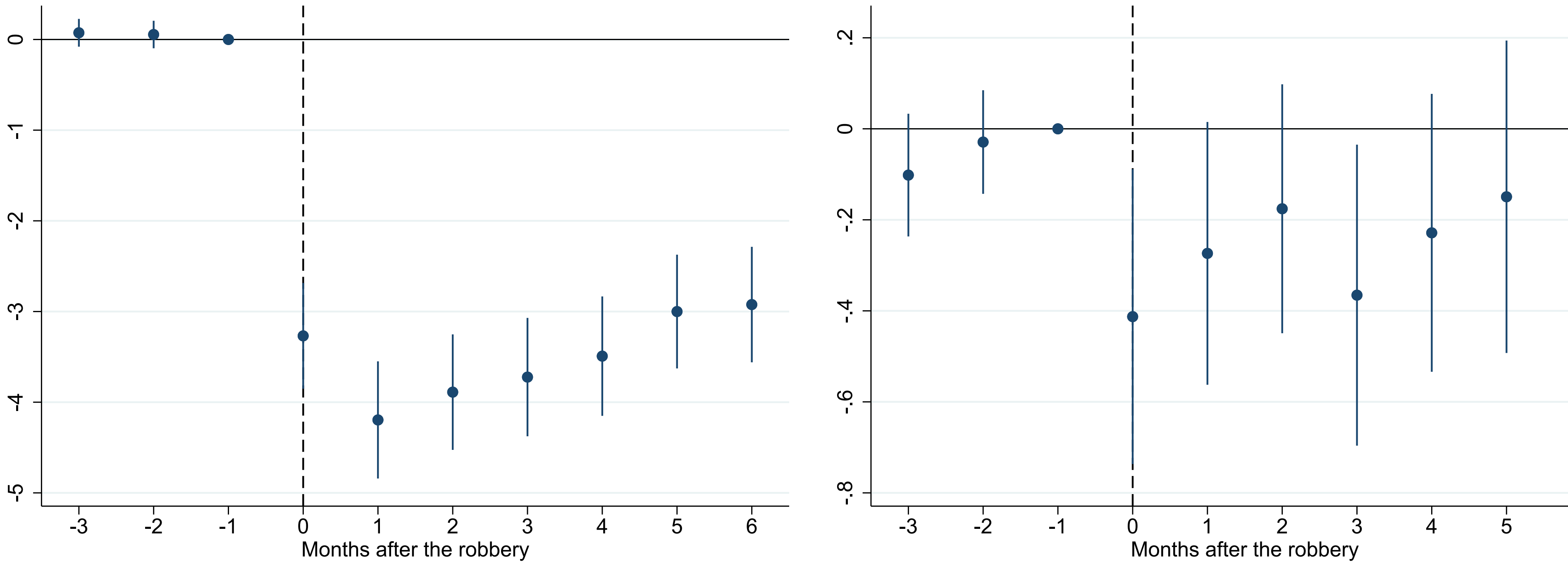
Figures

Figure 1: Municipalities That Suffered Bank Branch Robberies (2018-2021)



(**a**) Full Sample

(**b**) CEM Matched Sample

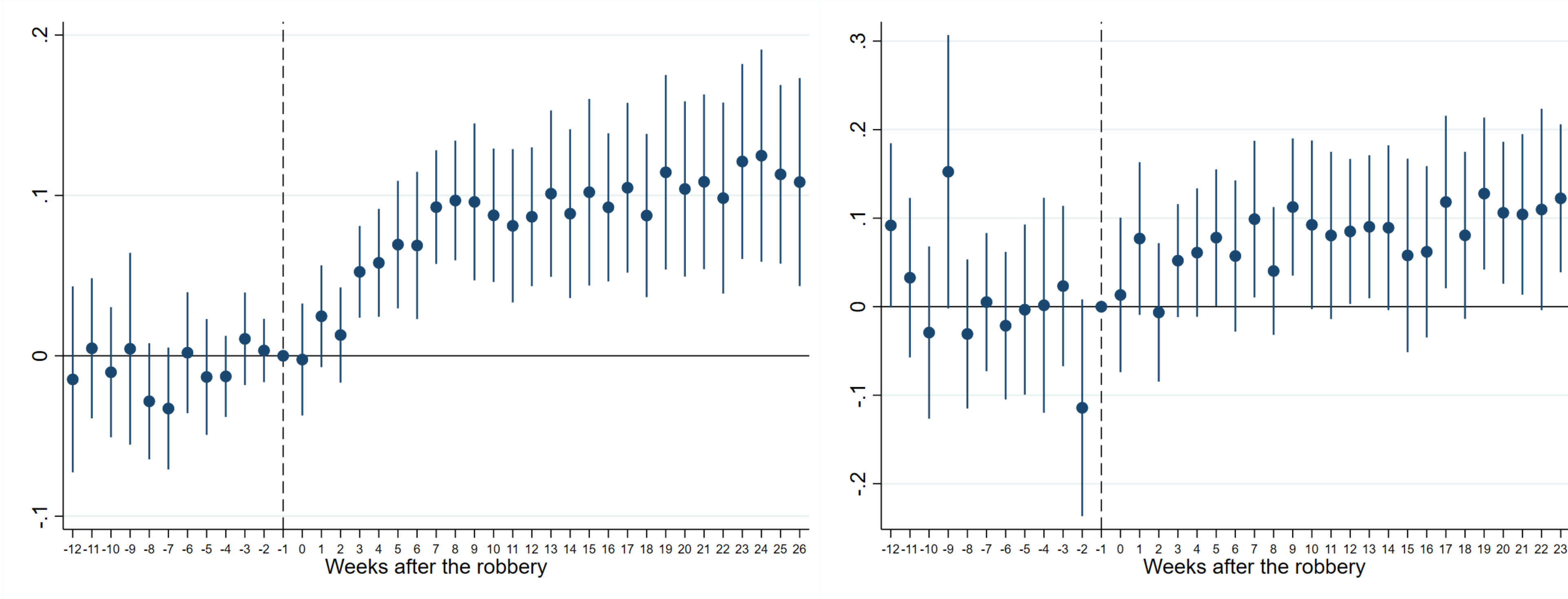


(**a**) Exposed branches

(**b**) Non-robbed branches

Figure 2: Bank Robbery and Branch Cash Inventory

Notes: i) Reported 95% confidence intervals are based on standard errors clustered at municipality level. ii) All specifications include bank-municipality and bank-time fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. iii) Regressions use the matched sample of Coarsened Exact Matching procedure and are weighted by the Coarsened Exact Matching weights.

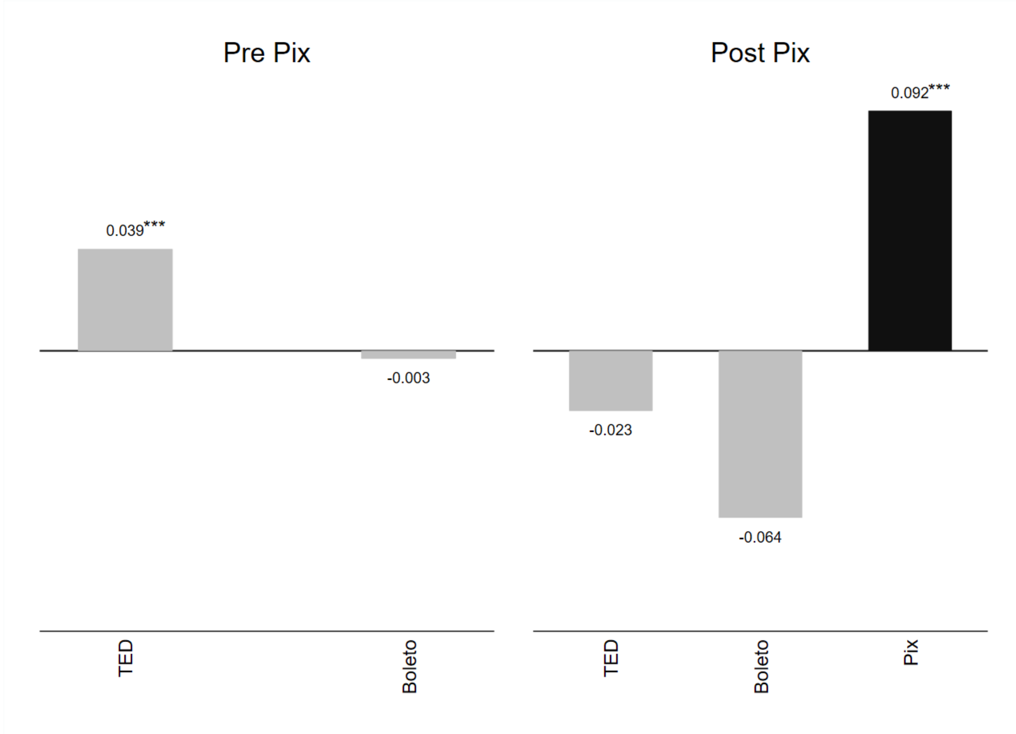


(**a**) Pix Transactions

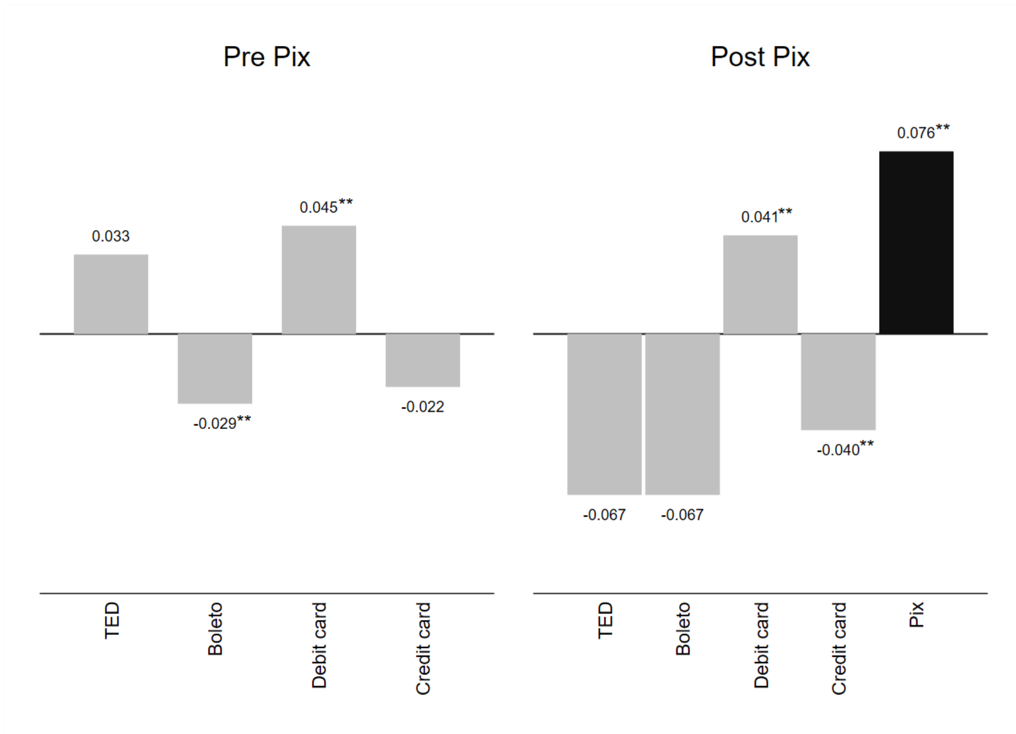
(**b**) Value Pix Transactions

Figure 3: Bank Robberies and Technology Adoption

Notes: i) Reported 95% confidence intervals are based on standard errors clustered at municipality level. ii) All specifications include municipality and time fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. iii) Regressions use the matched sample of Coarsened Exact Matching procedure and are weighted by the Coarsened Exact Matching weights.



(**a**) Number of Transactions



(**b**) Value of Transactions

Figure 4: Branch Robberies and Old Technology

Notes: i) Standard errors clustered at the municipality level. ii) All specifications include municipality and time fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage. iii) Regressions use the matched sample of Coarsened Exact Matching procedure and are weighted by the Coarsened Exact Matching weights. iv) * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix

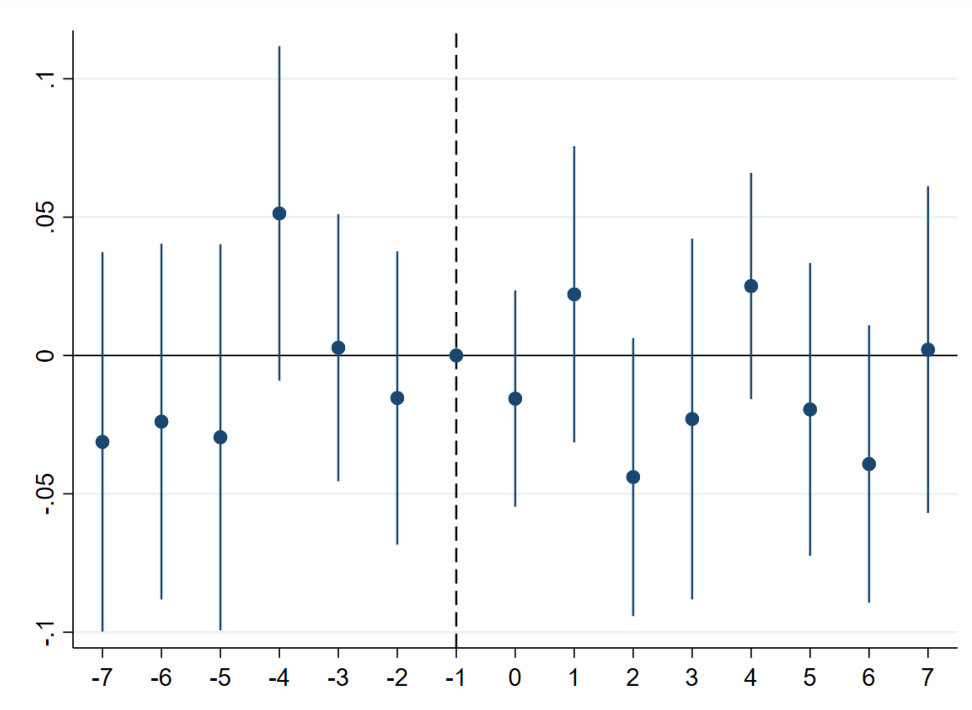
Figure A1: Example of a Banco do Brasil Branch Destroyed during an Attack in the State of Bahia

Source: https://atarde.uol.com.br/bahia/noticias/2164724-ataques-a-bancos-na-bahia-aumentam-mais-de-400-no-periodo-de-janeiro-a-abril

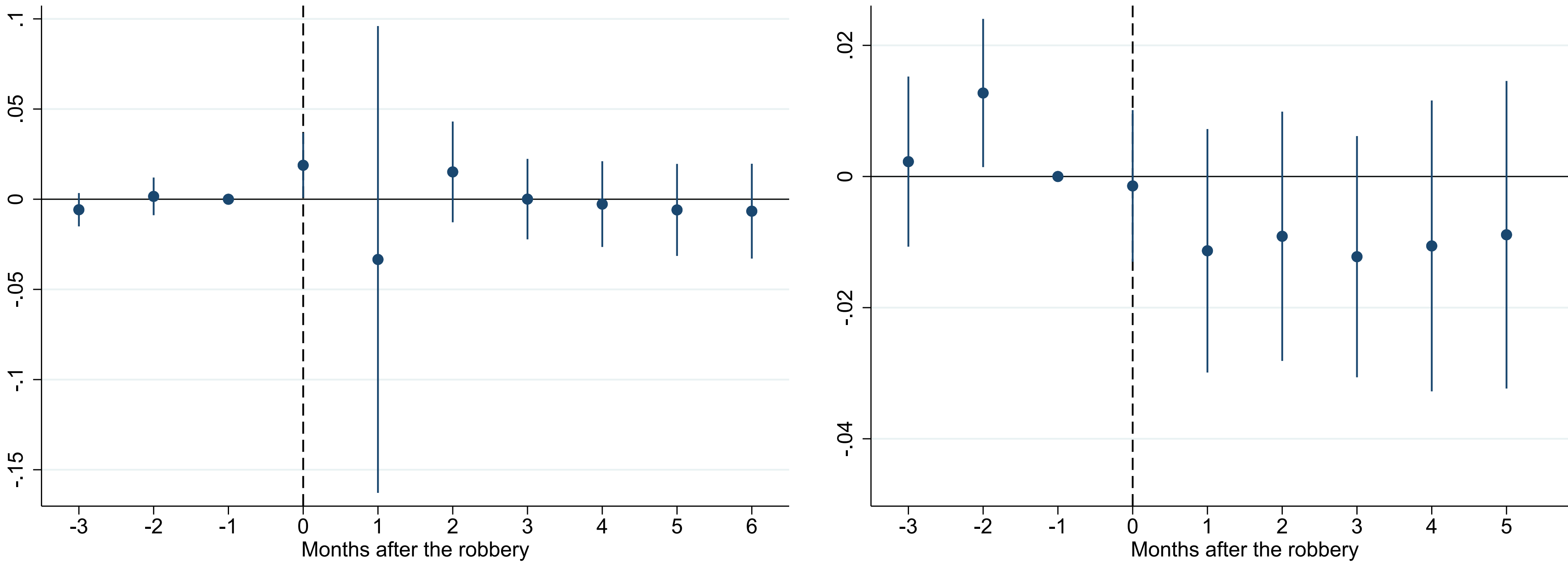
Figure A2: Example of a Banco Bradesco Branch Destroyed during an Attack in the State of Minas Gerais

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

Figure A3: Effects of Robberies on Homicides



Notes: i) Reported 95% confidence intervals are based on standard errors clustered at the municipality level. ii) All specifications include municipality and time fixed effects. iii) Regressions use the matched sample of Coarsened Exact Matching procedure and are weighted by the Coarsened Exact Matching weights. Due to a large number of zeros, we use as dependent variable the inverse hyperbolic sine transformation of the number of homicides.

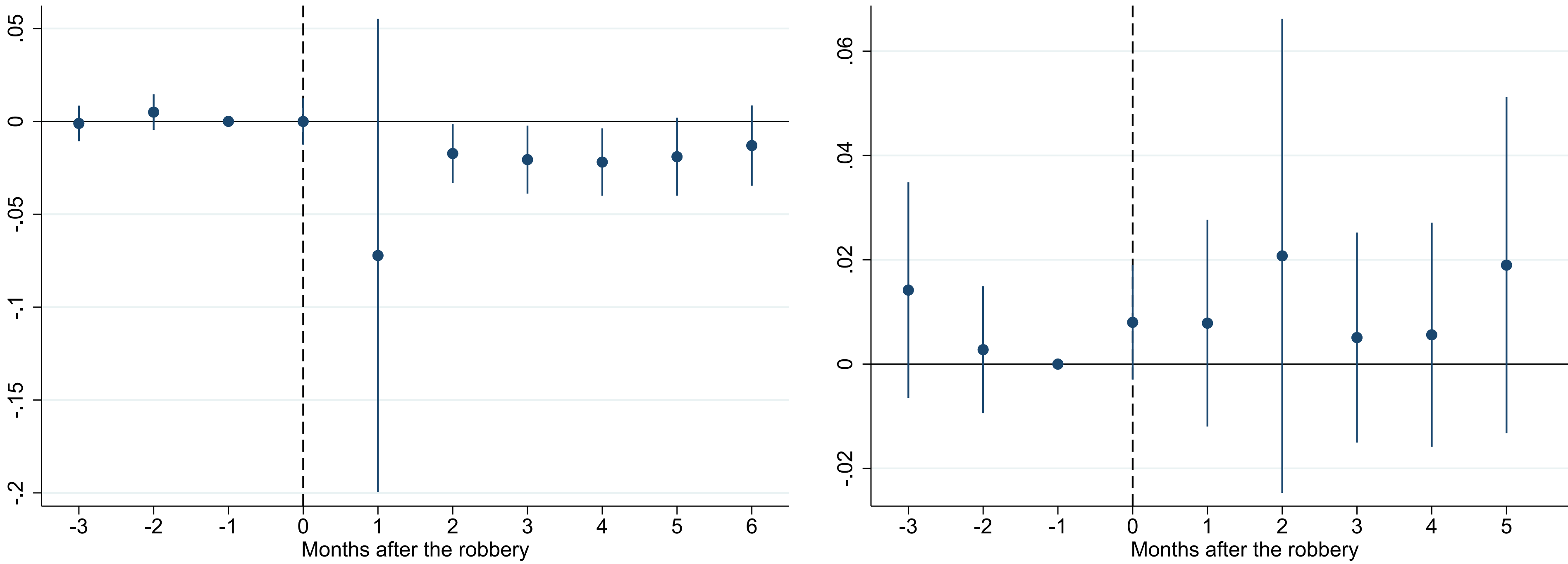


(**a**) Branches Exposed to the Robbery Lending

(**b**) Local Spillover Effects on Lending

Figure A4: Bank Robberies and Branches Lending

Notes: i) Reported 95% confidence intervals are based on standard errors clustered at the municipality level. ii) All specifications include municipality-bank and bank-time fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage.

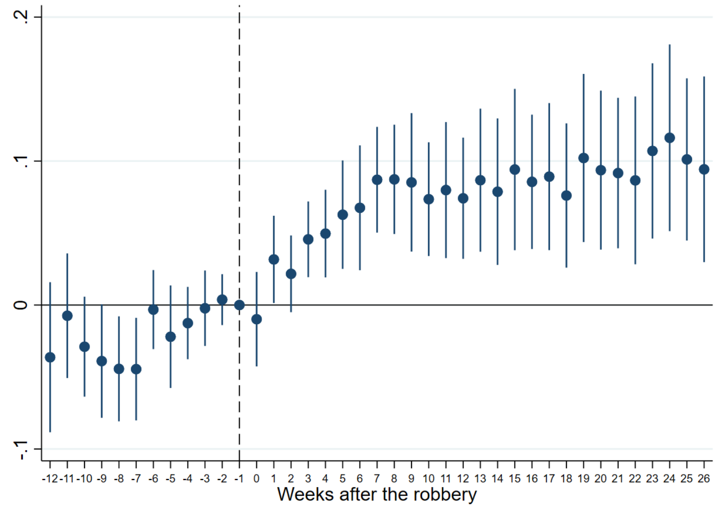


(**a**) Branches Exposed to the Robbery Deposits

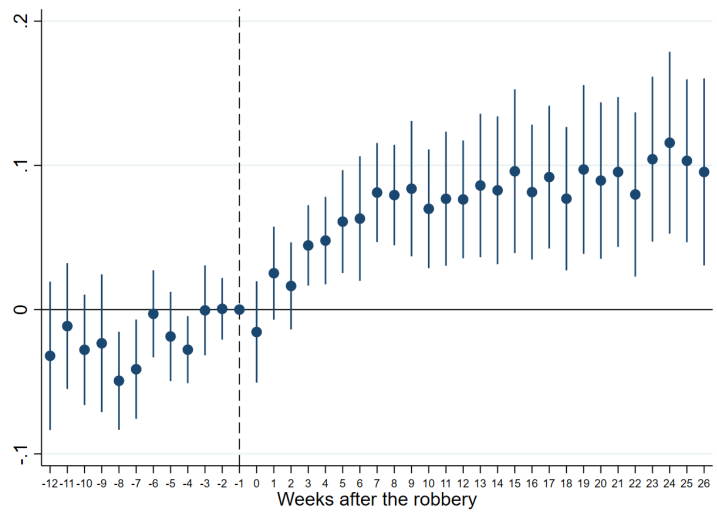
(**b**) Local Spillover Effects on Deposits

Figure A5: Bank Robberies and Branches Deposits

Notes: i) Reported 90% confidence intervals are based on standard errors clustered at the municipality level. ii) All specifications include municipality-bank and bank-time fixed effects as well as time-varying heterogeneous effects of municipal 3G Internet Population coverage.



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



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

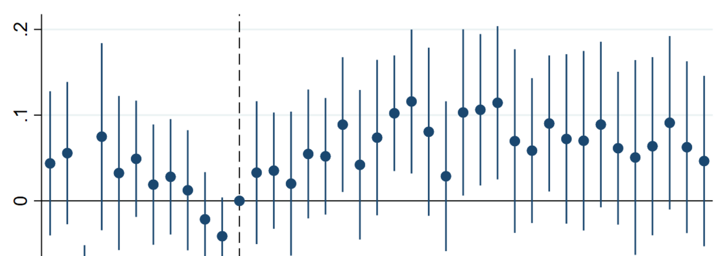


Table A1: Characteristics of selected means to make transfers in Brazil

	Clearing time	Type of transaction				Fees - individual		Fees - firm	
		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.

Sources of Information

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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.