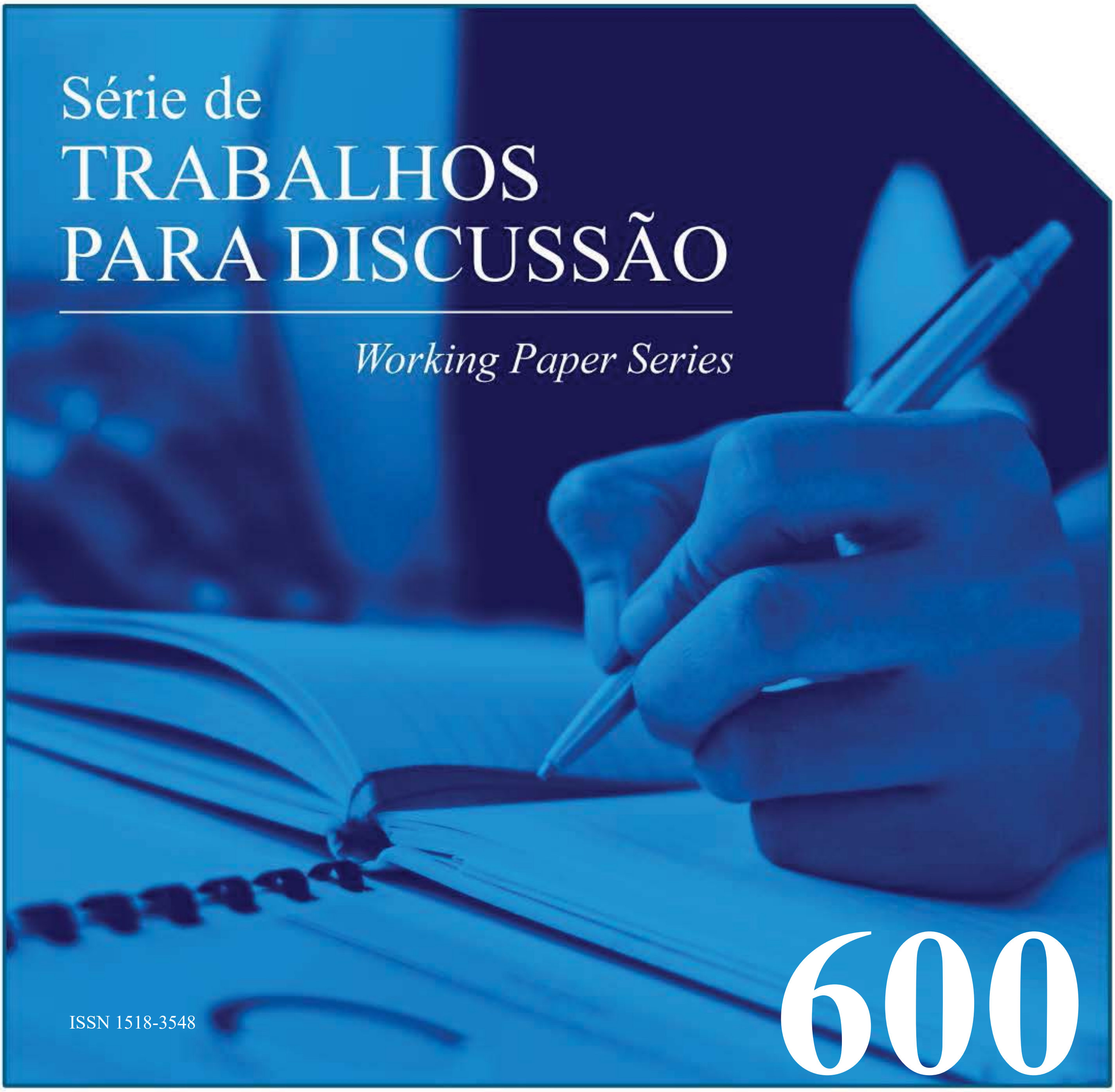

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Payment Technology Complementarities and their Consequences in the Banking Sector: evidence from Brazil's Pix

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Non-technical Summary

Payment technologies have long been recognized for their potential to enhance societal welfare, stimulate consumption, and drive economic growth. The literature documents these benefits across various innovations, such as mobile money, instantaneous transfers such as Pix, Zelle, and UPI, and card payments. However, despite their advantages, adoption rates for instant payment technologies remain sluggish, with costs exceeding 1% of GDP in many economies. One significant barrier to widespread adoption appears to be the resistance of established financial institutions that fear competition and loss of profits, leading to slow implementation and high fees.

This research focuses on evaluating the impact of Pix, an instant payment system launched by the Central Bank of Brazil, on other payment methods and the broader banking sector. To rigorously assess Pix's effects, this study employs an Instrumental Variables approach using floods as an instrument. Floods serve as a useful instrument due to their randomness, and significant impact on informal insurance needs, which Pix effectively facilitates. Preliminary analysis confirms that floods do not influence other payment methods or banking behaviors prior to Pix's introduction, supporting the instrument's validity. Post-Pix, floods trigger a sustained increase in Pix usage, with significant growth in remittances, highlighting Pix's role in aiding informal insurance networks.

Our findings reveal Pix complements other payment methods, driving growth in the use of the four most popular payment technologies in Brazil among individuals and firms. We find that a 1% increase in the number of active users of Pix increases the number of transactions of Bank Wire by 4.5% and by Payment Slips by 5.7%. Pix also spurs the acceptance of Debit Card transactions by 1.2%. In the banking sector, a 1% growth in Pix users increases the number of first-time bank users by 0.8% and first-time credit users by 0.4%. We also find that following a flood, the number of bank accounts being actively used grows by 4%. These improvements benefit both traditional and digital banks. Digital banks witness a higher surge in new account openings, whereas traditional banks observe a higher growth in account activity by firms.

This research contributes to policy debates by demonstrating the complementary nature of instant payment systems such as Pix and their potential to bolster the financial sector rather than disrupt it. It highlights the benefits of adopting such technologies and underscores their role in promoting financial inclusion and resilience. Academically, this study enriches the literature on payment technologies, banking competition, and informal insurance by showcasing the broad and multifaceted impacts of Pix on the Brazilian economy.

Sumário não Técnico

As tecnologias de pagamento têm sido amplamente reconhecidas por seu potencial para melhorar o bem-estar social, estimular o consumo e impulsionar o crescimento econômico. A literatura documenta esses benefícios em várias inovações, como o Mobile Money, transferências instantâneas como Pix, Zelle e UPI, e pagamentos com cartão. No entanto, apesar de suas vantagens, as taxas de adoção das tecnologias de pagamentos instantâneos permanecem lentas, com custos que excedem 1% do PIB em muitas economias. Um obstáculo significativo para a adoção generalizada parece ser a resistência das instituições financeiras estabelecidas que temem a concorrência e a redução de lucros, levando à implementação lenta e tarifas altas.

Esta pesquisa foca em avaliar o impacto do Pix, um sistema de pagamento instantâneo lançado pelo Banco Central do Brasil, em outros métodos de pagamento e no setor bancário mais amplo. Para avaliar rigorosamente os efeitos do Pix, este estudo emprega uma abordagem de Variáveis Instrumentais usando enchentes como instrumento. As enchentes servem como um instrumento útil devido à sua aleatoriedade e impacto significativo nas necessidades de seguro informal, que o Pix facilita efetivamente. A análise preliminar confirma que as enchentes não influenciam outros métodos de pagamento ou comportamentos bancários antes da introdução do Pix, apoiando a validade do instrumento. Após o Pix, as enchentes desencadeiam um aumento sustentado no uso do Pix, com crescimento significativo nas doações, destacando o papel do Pix em auxiliar redes de seguro informal.

Nossos resultados mostram que o Pix complementa outros métodos de pagamento, impulsionando o crescimento do uso das quatro tecnologias de pagamento mais populares no Brasil entre indivíduos e empresas. Verificamos que um aumento de 1% no número de usuários ativos do Pix aumenta o número de transações por TED em 4,5% e por Boletos Bancários em 5,7%. O Pix também funciona como um impulsionador da aceitação de transações com Cartão de Débito, com um aumento de 1,2%. No setor bancário, um crescimento de 1% nos usuários do Pix aumenta o número de novos usuários bancários em 0,8% e de novos usuários de crédito em 0,4%. Também constatamos que, após uma enchente, o número de contas bancárias ativamente utilizadas cresce em 4%. Essas melhorias beneficiam tanto os bancos tradicionais quanto os bancos digitais. Os bancos digitais observam um aumento maior na abertura de novas contas, enquanto os bancos tradicionais veem um crescimento maior na atividade de contas de empresas.

Esta pesquisa contribui para os debates de políticas públicas ao demonstrar a natureza complementar dos sistemas de pagamentos instantâneos como o Pix e seu potencial para fortalecer o setor financeiro em vez de desestabilizá-lo. Ela destaca os benefícios da adoção de tais tecnologias e sublinha seu papel na promoção da inclusão financeira e resiliência. Academicamente, este estudo enriquece a literatura sobre tecnologias de pagamento, concorrência bancária e seguro informal ao mostrar os impactos amplos e multifacetados do Pix na economia brasileira.

Payment Technology Complementarities and their Consequences in the Banking Sector: evidence from Brazil's Pix*

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September 12, 2024

Abstract

In this paper, we employ an instrument and individual-level banking data in Brazil to examine the effects of a novel payment technology, Pix, on the utilization of other payment technologies and its impact on the banking sector. We find evidence that Pix increases the usage of the four most common payment technologies in Brazil among individuals and firms. Furthermore, our empirical evidence suggests that Pix contributes to an increase in the number of bank accounts, their usage, and access to credit, benefiting different types of banks. The findings indicate that the implementation of new payment technologies yields advantages not only for firms and individuals but also for the broader banking and payment industry.

Keywords: Natural Disasters; Instant Electronic Transfers; Pix; Payment Technologies

JEL Classification: D14, E42, E51, E58, G20, O1, O16, O33, Q54.

The views expressed in this Working Paper are those of the authors and do not necessarily reflect those of the Banco Central do Brasil.

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1 Introduction

For a long time, payment technologies have been known to bring an array of different benefits to society. The payment literature is filled with evidence of the positive effects of new payment technologies on welfare, consumption, and economic growth from technologies such as Mobile Money, instantaneous transfers (e.g. Pix, Zelle, UPI, Swish) and card payments (Jack and Suri [2014], Higgins [2019], Bachas et al. [2018], Bachas et al. [2021] Balyuk and Williams [2021], Crouzet et al. [2023], Dubey and Purnanandam [2023], and Chodorow-Reich et al. [2020]). That is why more than 100 countries are experimenting with instantaneous payment technologies (Duffie [2022] and Frost et al. [2024]).

However, new payment technologies have faced opposition from skeptic players in the government and banking industry. They fear that an easy, cheap, and instantaneous way of transferring money could decrease the barriers to switching banks and substitute more profitable payment methods, thus increasing competition, decreasing profits, and disrupting the banking industry (Bogaard et al. [2024], Reserve [2022], and BIS [2020]). For example, the United States Congress passed a bill to stop the development of the digital dollar, and the biggest banks in the country delayed their participation in the new payment technology developed by the Federal Reserve, called FedNow[1] (Feltman [2019], Marek [2024], Marek [2023], and Versprille [2022]). However, these players seem to underplay the complementarities between payment technologies and financial services. For example, to use payment systems or financial services, individuals need to pay the fixed cost of learning how to use bank accounts. Thus, an improved payment method can make individuals face these fixed costs, increasing the use of bank accounts, financial services, and other payment methods[2]. The opposing forces of substitution and complementarity play a crucial role in determining the effects of new payment technologies on the banking sector.

Given the importance of payment technology and the resistance that it faces, this research estimates the effects of a new payment technology on other payment methods and, more broadly, in the banking sector. For this, we study Pix, the new instantaneous bank transfer launched in November 2020 by the Central Bank of Brazil (BCB) that only cost $4 million dollars to develop, generated a cost savings of $5.7 billion dollars in 2021 alone, and is expected to help generate 2% of Brazil's GDP by 2026 according to an ACI Worldwide study[3]. Pix is a technology for instantaneous bank-to-bank transfers [4] that quickly exploded in popularity in Brazil with 149 million people and 15 million firms using it as of December 2023. In contrast to the US Fed's approach,

[1] When FedNow launched in July 2023, just 35 out of over ten thousand financial institutions joined. By July 2024, this number had increased to around 800.

[2] One simple example is an attractive credit card offer. To enjoy this offer, individuals will be willing to pay the fixed cost of establishing a bank account which could lead them to deposit more money, acquire loans, and have access to a debit card.

[3] See ACI Worldwide study https://www.aciworldwide.com/wp-content/uploads/2022/04/Prime-Time-for-Real-Time-Report-2022.pdf

[4] All transactions for individuals are free. Banks can only charge fees for firms' transactions. During the beginning of Pix, most banks would not charge fees. As of December 2023, important Brazilian banks continue to make transactions for free for firms.

the BCB required all major banks to adopt Pix[5], making it ubiquitous in the country. At the same time, in Figure (1), we see that the proportion of cash transactions dropped from 42% in 2020 to 22% in 2023 and money in circulation dropped 10% during the same period. We also witness a growth in the use of other payment methods and financial services performed by banks, while the access channel used by the population to access bank services has shifted from physical access to cellphone access. At the macro level, we see the introduction of Pix seems to decrease the use of cash and accelerate the digitalization of payments and banking in Brazil.

In order to formally study the effects of Pix on the payment and banking sector, we leverage private individual-level data on the uses of payment and bank services for the entire population of citizens and firms in the country through the BCB. In the case of payment methods, the challenge is to empirically separate the substitutability or complementarity of Pix on other methods from changes in consumer preferences. In the case of the banking sector, we face the challenge of omitted variable bias. To solve those challenges, we use an Instrumental Variables approach and floods as our instrument. We argue that floods can be a great instrument for several reasons, first, like most weather events, floods can be considered random draws from the climate distribution when controlling the endogenous ex ante risk of flood in a municipality. Second, floods are a common and recurring natural disaster in Brazil, affecting 84% of the municipalities between 1991 and 2022, giving us statistical power. Third, floods are sudden and swift, making them difficult to predict. Fourth, we expect a strong first stage of floods affecting Pix usage through the informal insurance channel, as has been shown by other researchers showing the crucial role that instantaneous transfer methods play during shocks (Jack and Suri [2014], Blumenstock et al. [2016], Riley [2018]). Finally, we do not expect floods to affect other payment methods in Brazil because they are not suitable for informal insurance. Compared to Pix, they are more expensive, harder to use, slower, and available through fewer banks during fewer hours. Moreover, since the last payment method introduced in Brazil was decades ago, if floods were to affect long-term usage levels of payment methods, it would have already done so.

However, instead of blindly believing the exclusion restriction of our instrument, we begin our work by studying the effects of floods on our main variables before the launch of Pix. Our goal is to show that prior to Pix, the exclusion restriction used to hold. For our analysis, we examine the usage of payment methods, bank accounts, and bank services at the municipal level using a staggered differences-in-differences design. In this case, our empirical strategy relies on the Parallel Trends assumption based on never-treated units, which translates to our variables following a parallel trend when controlling for Municipality and (Time x Flood Risk) fixed effects in the absence of treatment (flood). Our Municipality fixed effect captures fixed spatial characteristics, and our Time-fixed effect interacted with Flood Risk allows us to capture any common trend to untangle idiosyncratic shocks to areas while permitting differential trends for municipalities with similar probability of floods.

We show that floods obey the exclusion restriction in the period before the introduction of Pix,

[5] The Central Bank imposed that any financial institution with more than 500 thousand accounts must join Pix, 38 of them were forced to join and more than 700 other banks and financial institutions choose to join at the launch.

meaning that floods do not affect the usage of other payment methods, bank accounts, or bank services prior to Pix's introduction. This increases our confidence in the validity of our instrument. We also graph the effects of floods in our variables after Pix is introduced to find that floods spark a continuous growth in the use of Pix with the number of active users of Pix increasing to more than 3%, and the number of transactions and value transacted among individuals and firms increasing 4-5%. Moreover, we show that after Pix was introduced, the usage of other payment methods, bank accounts, and banking services displayed a similar pattern, remaining stable immediately after a flood and then showing signs of growth after a few weeks. This pattern is consistent with our exclusion restriction assumption that floods do not directly impact our variables, and it is consistent with people and firms slowly switching to digital payments and services after they become active users of Pix.

To better quantify the effects of Pix, we turn to our Instrumental Variables approach. We study the effect of an increase of 1% in the number of active Pix users on the usage of other payment methods to find an increase of 5.7% in the number of Payment Slip transactions, an increase of 4.5% in the number of bank wire transactions and an increase of 1.2% in the number of firms accepting debit cards. We also find that an increase of 1% in the number of active Pix users in a municipality leads to an increase of 0.45% in the number of people creating a credit relationship, a 0.25% increase in the number of people creating a relationship with a new bank, and a 0.80% increase in the number of people opening bank accounts for the first time.

Moreover, we expand our results on the creation of bank accounts by studying the behavior of people and firms that already have bank accounts. First, instead of counting bank accounts, we count the number of accounts that are actively used using transaction data. This is especially relevant to Brazilians since they have a massive number of bank accounts due to employers being able to dictate over employees' choice of bank. By the end of 2023, Brazilians averaged 6 accounts per person, a big growth from 3.5 accounts in 2020. We find that the number of active bank accounts grows more than 4% for people and 2% for firms following a flood. Second, we study self-transfers, which are defined as transfers between accounts owned by the same person or firm but in different banks. Since Brazilians have so many bank accounts and each bank account has its different benefits and comparative advantages, we believe that self-transfers are a good proxy for the optimization of bank accounts. We document a growth of active users of self-transfers of more than 4% for people and firms following a flood.

To address the belief that instantaneous payment technologies would make traditional brick-and-mortar banks obsolete and that digital banks and fintechs would take over, we study how the benefits to the banking sector are distributed among those two types of banks. First, we study Pix transactions to find that the growth in Pix popularity was shared almost equally between digital and traditional banks for people. For firms, we present evidence that seems to indicate that traditional banks were favored over digital banks. This is consistent with the fact that traditional banks are more established and can offer more complex services to firms. Second, we study the growth in the number and active use of bank accounts. We find evidence that the growth of new accounts seems to favor digital banks, while the growth in active use of accounts seems to favor traditional banks in the case of firms. This is consistent with the fact that smaller digital banks have more room to grow their number of accounts, while traditional banks have more to gain from an increase in the number of active users.

Finally, we study the mechanism that makes Pix popular after a flood. We investigate whether people would use Pix as an informal insurance tool after a natural disaster. We study remittances, which we define as a transaction between two people in different municipalities to find that, during the week of the flood, there is a significant drop in the outflow of money, while the number of inflow transactions increases together with the number of people outside the municipality that are sending money to people inside the municipality affected by the disaster. We document a permanent change in behavior following the flood, with remittances growing around 2-4% after a year, and a network effect of Pix, with people outside the municipality growing their use of Pix to send money.

Taken together, our results suggest that the introduction of Pix in Brazil has led to a financial revolution, with significant growth in bank accounts, bank services, and other payment methods. We also find the crucial role that Pix plays during an economic shock, acting as an informal insurance tool. Moreover, we shed light on the benefits that different types of banks receive from Pix, with digital banks expanding their number of accounts and traditional banks expanding their number of active accounts. Our results suggest that fears of the substitution of other payment methods and the disruption of the banking sector are unfounded, with much to be gained not only by people and firms but also by the payment and banking sectors.

Our research directly contributes to the policy debate on whether new low-cost instantaneous payment systems could hurt the payment and banking industry. This debate has delayed or completely stopped the development of new payment technologies in several countries. Our work contributes to this debate by showing the complementarities between Pix and other payment methods while also showing the increase in the use of bank accounts and bank services.

Academically, we make three major contributions. First, we add to the payment literature by studying the benefits and complementarities of different payment methods. Many articles have been written displaying the benefits of payment methods on welfare, consumption, and economic growth (e.g., Jack and Suri [2014], Suri and Jack [2016], Riley [2018], Aron [2018], Balyuk and Williams [2021], Koont et al. [2023], Wang, Bian et al. [2023], Brunnermeier et al. [2023], Garratt et al. [2022], Haendler [2022], Aker et al. [2020], Brunnermeier et al. [2019], and Dubey and Purnanandam [2023]). Another related literature on payment adoption studies how shocks can help overcome adoption barriers such as coordination failures, fixed costs, and lack of trust (e.g. Rosenstein-Rodan [1943], Rochet and Tirole [2006], Katz and Shapiro [1986], Huynh et al. [2022], Higgins [2019], Bachas et al. [2018], Bachas et al. [2021], Chodorow-Reich et al. [2020], Crouzet et al. [2023], Lahiri [2020], Gupta et al. [2020], and Breza et al. [2020]). We add to the literature by not only showing how a shock can increase the popularity of a payment technology but also that it can complement different payment methods, increasing the use of other beneficial payment methods and accelerating the digitalization of the economy.

Second, we add to the bank competition literature by studying the effects of a payment method in the banking sector. A growing literature studies the effects of new technologies in the banking sector (for example Ouyang [2021], Yannelis and Zhang [2023], Beaumont et al. [2022], Babina et al. [2023], Parlour et al. [2022], Gopal and Schnabl [2022], Di Maggio and Yao [2021], Chava et al. [2017], Ghosh et al. [2022], Erel and Liebersohn [2022], Buchak et al. [2018], Berg et al. [2022], Sarkisyan [2023], and Argentieri Mariani et al. [2023]). We add to the literature by showing that instantaneous payment methods can lead to the expansion of bank accounts, account use, access to credit, and bank services. In addition, we expand our research to show how these benefits are spread across different types of banks.

Third, we add to the literature on natural disasters and informal insurance by studying the role of Pix as an informal insurance tool. Informal insurance networks have been studied by a extensive literature to bring an array of benefits, especially for the most vulnerable families (e.g. Jack and Suri [2014], Dell et al. [2014], Blumenstock et al. [2016], Riley [2018], Balyuk and Williams [2021]). We add to the literature by showing that shocks can lead to a long-term change in informal insurance behavior and that the use of a new informal insurance tool is spread to other municipalities through people's networks.

The remainder of the paper is organized as follows. Section (2) describes the institutional background, informing in more detail the payment technologies in Brazil and our instrument, floods. Section (3) describes our main data sources. Section (4) describes our empirical strategy. Section (5) presents our main results. Section (6) presents our robustness checks. Section (7) concludes.

2 Background

In this section, we familiarize the reader with the Brazilian banking and payment landscape, the history of floods in Brazil, and compare the Pix initiative with other countries.

2.1 Payment Technology in Brazil

Like many countries, Brazil lacked a modern way to transfer money between bank accounts and make payments. Almost 20 years after the last major innovation in this area, the BCB developed Pix in November 2020 with the goal of allowing users to make transfers and payments in a few seconds, 24 hours a day, seven days a week. In essence, Pix is an instantaneous transfer method between bank accounts[6] that is completely free for individuals. Firms may incur a small percentage fee for transactions that varies among financial institutions[7]. However, some of the most important financial institutions in Brazil still do not charge fees for Pix transactions.

[6] We use term "bank account" to refer also to payment accounts used by fintechs and payment institutions.

[7] In this paper, the terms "financial institutions" and "banks" are used interchangeably. These terms encompass financial institutions in general (including banks and credit unions) and payment institutions.

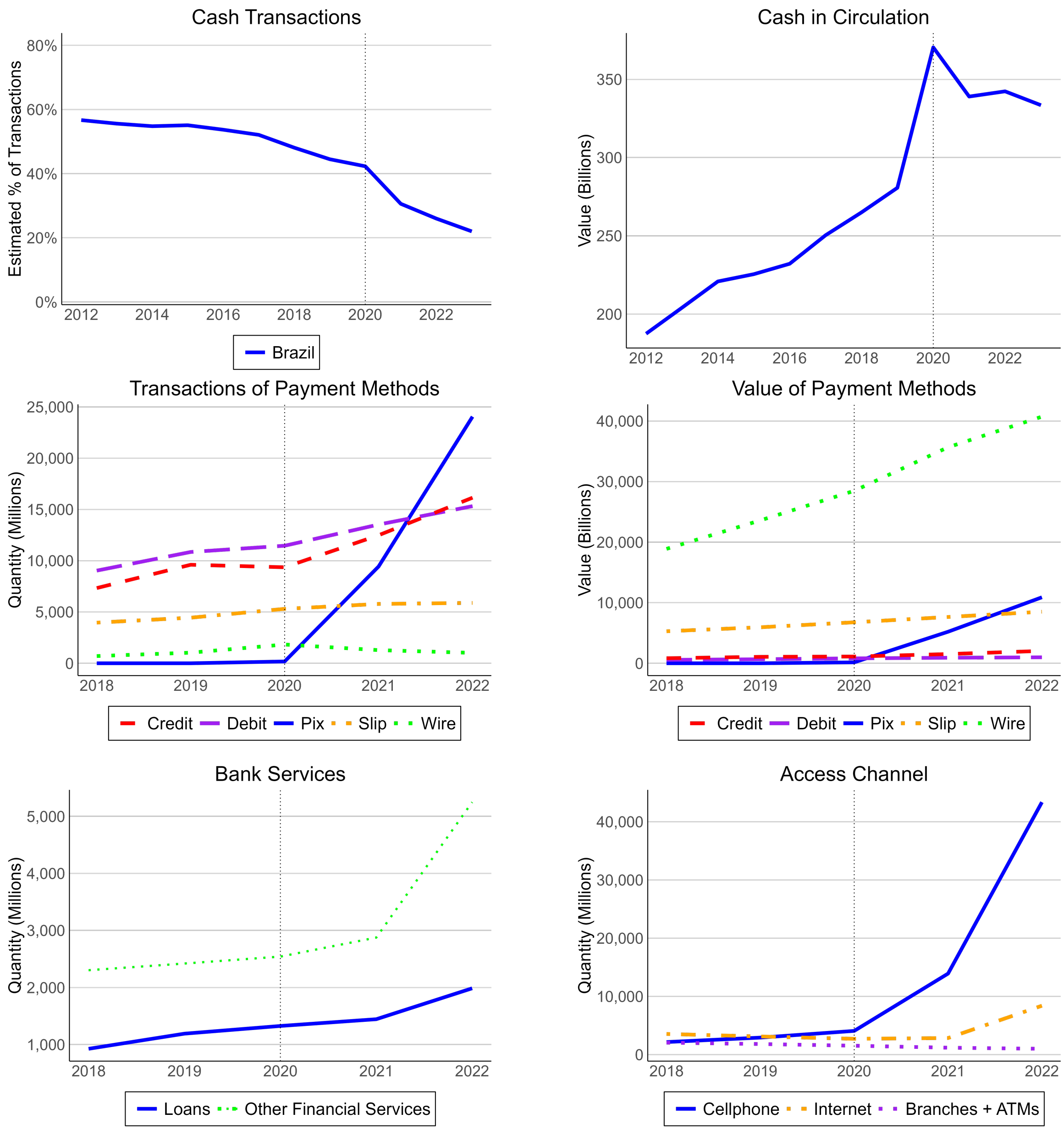


Figure 1: Time Series of Macro Variables in Brazil. Source: BCB.

To use Pix, senders would initiate a transaction by inputting the receiver's key into their bank mobile app. The key uniquely identifies the receiver and takes the form of a phone number, email, random key, QR code or tax identification number[8]. The receiver can also initiate a transaction by generating a dynamic QR code with embedded identifiers and the value of the transactions. This allows for payments to be instantly verified without the need for a manual check of bank balances, thus facilitating in-person and online purchases.

Pix gained popularity due to its speed, convenience, smaller fees, and for being present in most banks in Brazil since its inception (more than 800). By December 20, 2023, 149 million people and 15 million firms had used Pix, and it became the most popular transaction method in Brazil, surpassing cash according to a McKinsey study (Bretas [2023]). In 2023, $3.5 trillion dollars, almost twice the Brazilian GDP, were transferred in 42 billion Pix transactions, averaging 200 transactions per capita.

According to a McKinsey report, there seems to be a clear substitution from cash to Pix, but it is hard to tell whether Pix substitutes for other payment methods. We investigate the other four most popular payment methods in Brazil: Bank Wire (TED), Payment Slip (Boleto), Credit card, and Debit card. Bank Wire (TED or electronic funds transfer) is a system similar to Pix that permits fund transfers between bank accounts. For the transfer, users would need all bank information from the recipient, the transfer could take from a few minutes up to the end of the day, and it only works during business hours.[9] Additionally, there are around only 100 institutions able to do TED compared to the more than 800 institutions able to do Pix, and users are usually charged an expensive flat fee for transactions, so the method is more common for large transfers, especially between firms.

Boleto is a payment method that consists of a voucher with a unique barcode. It differentiates from TED because of it has a smaller flat fee, it does not require a bank for the sender, and it allows for instructions inside the voucher, for example, extra fees for late payment. Boleto is a very popular P2B payment method, often used for utility bills and online purchases. However, this instrument takes up to 3 days to clear, it only works during business hours, and there is a limited number of banks that offer this service.

Credit card is a very useful payment method that allows consumers and firms to make secure transactions in person and online. Firms incur fixed costs to set up card payments and large percentage fees are taken for each transaction. Firms may also have to wait for 30 days to receive their money, with usually the option to pay extra fees to receive the money in a day. Users usually need access to a credit line with a bank and need to pay annuities. Debit card is similar but firms pay smaller fees compared to credit cards and receive the money earlier, and users do not need a credit line and have their money discounted from their bank account right away.

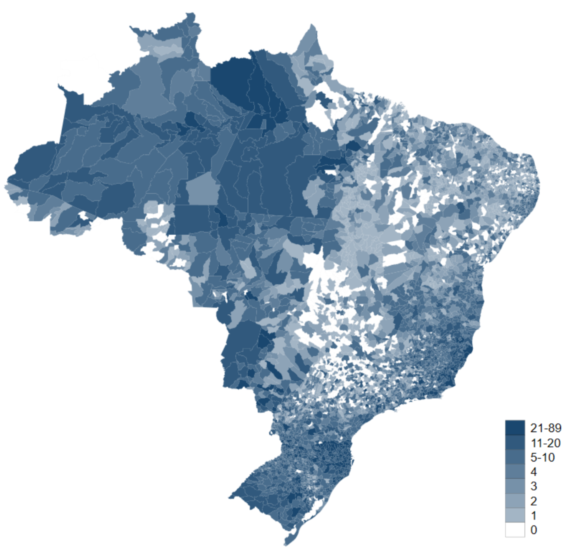
[8] Those are CPF for individuals and CNPJ for Firms. These numbers are not as sensitive as their American equivalent SSN and EIN. CPF and CNPJ are how we uniquely identify everyone in our research.

[9] Business hours are usually defined as 8 am to 5 pm on business days. Transfers outside those hours will only be processed the next business day, thus incurring extra days to the normal clearing time.

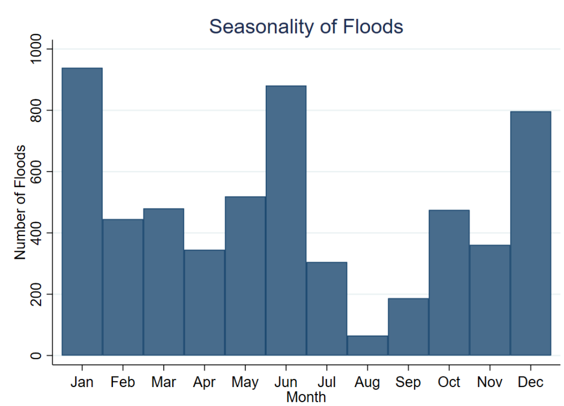
2.2 Flood

According to the World Health Organization, floods are the most frequent type of natural disaster in the world with 2 billion people affected between 1998 and 2017. In Brazil, floods are one of the most common natural disasters along with droughts. They happen suddenly, and swiftly and affect most parts of the country, with 84% of municipalities being impacted between 1991 and 2022. More than 6000 disasters occurred in the last 10 years, with floods happening all year long - look at Figure (2). It is estimated that they caused more than 2 thousand deaths, 140 thousand hospitalizations, and 16 billion dollars in losses; of those losses, only 1.2% were covered by federal assistance. It is also important to notice that in Brazil, the money given by the government following a natural disaster cannot go directly to the people affected, it must be used for "civil and defense" expenses (e.g. infrastructural projects).

To identify when a flood occurred, we use the natural disasters reports by the National System of Civil Protection. Those reports are filled by municipalities to inform damages to federal authorities[10]. The federal authorities then access the veracity of the information and help the municipality with logistic and financial support. We collect data on municipalities that were able to claim State of Emergency or State of Public Calamity due to floods from 1991 to 2022.



(a) Floods by Municipality - 1991 to 2022



(b) Floods by Month - 2013 to 2022

Figure 2: Floods in Brazil. Source: SINPDEC.

[10]There are subtle differences between the classification of a flood by the federal authorities depending on the cause of the flood. For simplicity, we aggregate those disasters under the term flood. They are "Alagamentos" (overflow of water at certain areas), "Inundações" (overflow of water from a body of water), "Enxurradas" (water running off at high speed), and "Tempestade Local/Convectiva" (local storms/convective storms with possibly intense rain, hail, wind, and lightning).

3 Data

To study payment methods, we collect identifiable individual-level data on Brazil's top 5 most used payment methods: Pix, Payment Slip (Boleto), Bank Wire (TED), credit card, and debit card. For Pix, we collect transaction-level data from the Instant Payments System (SPI) from its launch in November 2020 to December 2022[11]. From there, we generate weekly data for transactions, value transacted, and unique users. In order to investigate informal insurance, we collect data on remittances between people outside the flooded municipality and people inside it, thus being able to see how this mechanism plays a role in the expansion of Pix following a flood. Moreover, we investigate which banks are being used the most to make Pix transactions and whether people are using Pix to self-transferring funds from one type of bank to another.

For Payment Slip, we collect all individual transactions from the Interbank Payments Chamber (CIP)[12] from 2019 to 2022. We aggregate the data weekly at the municipality level to generate the number of transactions, value transacted, and unique users.

For Bank Wire, we collect all transactions from the Booking Transfer System (STR) and Funds Transfer System (SITRAF)[13] from 2019 to 2022. Similarly, we aggregate data weekly at the municipality level to generate the number of transactions, value transacted, and unique users.

For credit and debit card acceptance, we collect data on the volume of transactions at the firm and date level[14] from CIP from 2019 to 2022. Note that, differently from Pix, Boleto, and TED, we do not have transaction-level data for credit and debit cards. Thus, we will only know which firms accepted card payments, and the total value transacted at that date. Therefore, we will construct a measure of how many firms are accepting card payments, and the total value transacted in each municipality and week.

For financial services data, we collect data on every credit relationship between financial institutions and individuals and firms from the Credit Information System (SCR) from 2019 to 2022. This dataset identifies the lender (bank) and the borrower (firms and individuals) in each credit relationship. The data set reports a set of loan and borrower characteristics, including loan amount, type of loan, credit line, interest rates, and repayment performance. Since the use of credit cards is a form of loan, we are also able to access the number of people and firms with credit cards, and their total credit card balance.

To study people and firms' behaviors toward bank accounts, we collect data on bank account opening and closing dates by institution and account holder from the Client Registration in the National Financial System (CCS) from 2019 to 2022. With this dataset, we are able to see based on their unique ID which individuals and firms opened or closed bank accounts each day for each bank ID, when they opened their first account, and their current stock of accounts.

[11] SPI has all transactions except transactions internal to the banks.

[12] CIP is a non-profit civil society clearinghouse that is part of the Brazilian Payments System that operates the SILOC (Sistema de Liquidação Diferida das Transferências Interbancárias de Ordens de Crédito), where the Boletos are cleared.

[13] STR is operated by the BCB, while SITRAF is operated by CIP. STR and SITRAF do not register transactions internal to the bank.

[14] This dataset does not include store-branded cards nor meal vouchers.

As mentioned before, our flood data come from natural disaster reports filled by municipalities to the National System of Civil Protection. We collect data on municipalities that were able to claim a State of Emergency or State of Public Calamity due to floods and were verified by the government from 1991 to 2022. We use this dataset to determine when a flood occurred in order to use it as our instrument.

We collect monthly balance sheet data from each bank branch in the country. This dataset is known as ESTBAN (Estatística Bancária Mensal), which is compiled by the BCB every month. We use the confidential version of this dataset to have access to extra variables, such as deposits by people and firms, loans, physical cash inventory, and assets[15]. Our data spam all months from 2019 to 2022.

Municipality-level data are compiled from multiple sources, the Brazilian Institute of Geography and Statistics (IBGE) and Anatel being the main ones. From these databases, we can create control variables that vary over time to complement our fixed effects such as the municipality's population, GDP, taxes collected, education statistics, and internet access.

4 Methodology

4.1 Staggered Differences-in-differences

The first step to evaluate the effect of Pix on other payment methods is to find a good instrument, and we believe that floods can be this instrument (we will discuss this in the next section). To increase the credibility of our exclusion restriction, we show that, prior to Pix, floods did not affect the usage of other payment methods. We also show that the effect of floods on other payment methods is not immediate, which is consistent with the idea that floods affect the usage of Pix first, and then the usage of other payment technologies later.

For that, we use a methodology called Staggered Differences-in-differences, where floods are the event that triggers Pix adoption. One of the reasons why we would expect floods to affect the use of Pix is because of informal insurance. The literature has shown that people form informal insurance networks so that if a member of that network suffers a shock, people try to insure them by sending money. For example, Blumenstock et al. [2016] showed that, after a natural disaster, people make transfers to people affected by the shock; Jack and Suri [2014] also showed the importance of transfer technology in increasing their informal insurance network. We expect Pix to be used in those situations because of its lower price, speed, and convenience. Compared to other payment methods, the only one that could be used in the case of remittances is TED; however, the high flat price of TED transactions combined with its hard-to-use interface, limited availability, unpredictable transfer duration, and sparse number of participating banks makes TED an improbable candidate for informal insurance. We also believe that floods should not change long-term behavior towards older technologies because of the high frequency of floods in Brazil. Our ratio-

[15] Our cleaning of this data is similar to Bustos et al. [2020], we define bank deposits as the sum of deposits in checking accounts, savings accounts, and term deposits as reported by the ESTBAN dataset of the Central Bank of Brazil.

nale is that if people and firms were to change their behavior towards older technologies because of a flood, they would have done so already.

Like most weather events, floods can be considered random draws from the climate distribution in a given spatial area. We follow the literature on extreme weather events, summarized in Dell et al. [2014], to evaluate the effect of floods in a municipality in Brazil. In this literature, it is assumed that the occurrence of a flood is a random event when comparing regions of similar probability of flooding. Thus, the likelihood of being flooded ex-ante is endogenous and controlled for, while being flooded is exogenous and allows identification.

The main assumption of this approach is the conditional Parallel Trends assumption based on never-treated units. This assumes that, without treatment, treated units would move parallel to never-treated ones. Due to our Municipality and Time x Flood Risk Fixed Effects, our assumption translates to similar municipalities with similar flood risk moving parallel in the absence of a flood.

$$y_{m,t} = \sum_{k \neq -1} \beta_k Z^k_{m,t} + \mu_m + \theta_{Risk,t} + \epsilon_{m,t} \tag{1}$$

In Equation (1), $y_{m,t}$ is the variable of interest measuring the use of a type of payment technology or the use of a banking service in municipality m at time t (e.g. log Pix users or log quantity of bank accounts). Municipality-fixed effects μ_m capture fixed spatial characteristics, untangling the impact from various potential sources of omitted variable bias. Time fixed effect interacted with Flood Risk $\theta_{Risk,t}$ allows us to capture any common trend to untangle idiosyncratic shocks to areas while permitting differential trends for municipalities with similar probability of floods. In our case, we define Flood Risk using ex-ante flood occurrences from 1991 to 2018, we divide municipalities into quintiles based on those numbers. The first quintile contains the municipalities that were never flooded, and the fifth quintile contains the most flooded municipalities. This allows us to compare municipalities with similar probabilities of getting flooded to each other and allows for differential trends in those groups to account for the endogeneity in the risk of floods. $Z^k_{m,t}$ is a dummy that equals 1 if municipality m was hit by a flood k weeks ago. ϵ_{mt} is the error term. For our primary analysis, we decided to use a simpler Two-Way Fixed Effects regression model (TWFE) without the inclusion of control variables. We believe it is better to show the most straightforward results first, and then change the model and add controls later to see if the results are robust.

We analyze two different periods, the "Before Pix" and the "After Pix". The period "Before Pix" consists of January 2019 until November 16, 2020, and the period "After Pix" consists of November 16, 2020 until December 20, 2022. As a robustness check, we also use the period from March 2020 until November 16, 2020 as "Before Pix", and the period from November 16, 2020 until June 2021 as "After Pix". This is to test whether the results are robust during the Covid period. We include all weeks before and after the shock; however, we only graph results from -26 to +52 weeks. We also show results by balancing the sample, so that every treated municipality has equal weight in the data points shown. We use data on all municipalities and cluster the standard errors at the municipal level.

4.2 Instrumental Variable

Once we show that floods affect the usage of Pix, we move on to establish that it is reasonable to believe the exclusion restriction that is, floods do not affect other payment technologies directly. We believe this assumption for three reasons; the first one is that other payment technologies are not suitable for informal insurance, they are expensive, hard to use, and slow; the second one is that it is reasonable to believe that if floods affected the usage of payment technologies, it would have done so already since floods are very common and the other technologies have been around for decades; and the third is that we have evidence that floods did not affect the usage of other payment technologies before Pix was introduced. Thus, we can use floods as a suitable instrument for the increase in usage of Pix and not the others.

$$y_{m,t} = \delta Pix_{m,t} + \mu_m + \theta_{Risk,t} + \epsilon_{m,t} \tag{2}$$

$$Pix_{m,t} = \beta Z_{m,t} + \mu_m + \theta_{Risk,t} + \nu_{m,t} \tag{3}$$

In Equation (2), $y_{m,t}$ is the variable of interest measuring the use of a type of payment technology or the use of a banking service in municipality m at time t. Municipality-fixed effects μ_m, Time-fixed effects by subgroup $\theta_{Risk,t}$ are added. $Pix_{m,t}$ measures the use of Pix in municipality m at time t. In Equation (3), $Z_{m,t}$ is the instrument, a dummy that equals 1 if municipality m was hit by a flood on a time before or equal to t, and 0 otherwise. We use the same periods as before and we cluster errors at the municipality level.

5 Results

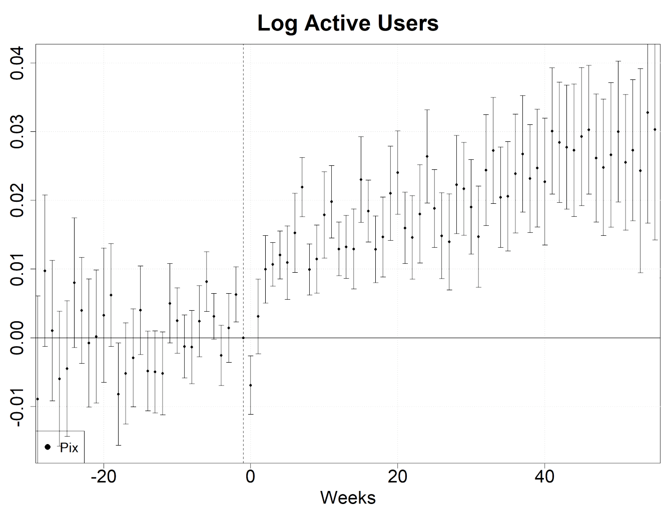
5.1 Effects of Floods on Pix

The advantage of the staggered differences-in-differences approach is that, rather than believing assumptions blindly, we can see them playing out. Our main variable of interest is the active number of Pix users in a municipality. We define it as 1 if a person received or sent money using Pix in a given week and 0 otherwise. The idea behind the choice of this variable is that floods would increase the use of Pix through a channel of informal insurance (we will explore this channel in Section 5.4), and once people pay the fixed costs of using Pix, such as setting up an account and learning how to use the app, they will continue to use it. Moreover, since those fixed costs are shared with other payment methods, we expect that the increase in the use of Pix would increase the use of other payment methods as well.

For this analysis, we run Equation (1) on the logarithmic quantity of active users of Pix. Figure

(3) shows the staggered differences-in-differences graph on the left. In the figure, we show that the number of people using Pix drops significantly during the week of the flood, which is consistent with a drop in commercial activities during a natural disaster; however, an upward trend begins a week after the disaster and continues over the course of the year. In the graph, we can see that the number of active Pix users increases to more than 3% after 52 weeks. On the right of Figure (3) we show the results of the first stage of our IV approach where we performed Equation (3). In the table, we find consistent results with floods increasing users by 2.2%.

We provide a more detailed analysis of the effect of floods on many Pix variables in Figure (8) found in the Appendix. In this analysis, we distinguish transactions received and sent by people and firms. In the graphs shown in the figure, it is possible to see that the drop in the use of Pix on the week of the flood is mostly due to a drop in the number of transactions sent. This behavior is consistent with the need to save money during a natural disaster. Another interesting result is the fact that the number of transactions sent by people increases more than the number of transactions received, whereas the number of transactions received by firms increases more than the number of transactions sent. Meanwhile, the growth in total value sent and received is similar. This is consistent with people using Pix to purchase many small-ticket items and services from firms, while firms perform a few high-ticket transactions to pay suppliers and workers' salaries. In numbers, we see an increase of 4-5% in the number of transactions and value transacted among people and firms.



	Dependent variable:
	Log Pix Users
	OLS
Flood	0.022***
	(0.006)
Mun. FE	*Yes*
Time x Region FE	*Yes*
Observations	614,163
R^2	0.995
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 3

Overall, we find that floods have a positive, progressive, and long-lasting effect on the use of Pix by people and firms. The effect is almost immediate, with usually a drop during the week of the flood and then a continuous growth in use in the following weeks. This is consistent with the idea that people use Pix as a form of informal insurance. Firms are quick to adapt as well, with growth, especially in the number of transactions received, which is consistent with people using Pix to purchase goods.

5.2 Effects of Pix on other payment methods

In this subsection, our goal is to establish a causal link between the number of active users of Pix and the use of other payment methods. The way we do this is two-fold. First, we show the effect of floods on other payment methods before and after Pix was introduced. The goal here is to demonstrate that before Pix, floods did not affect the usage of other payment methods, whereas after Pix, floods had a positive effect on the usage of other payment methods. Thus, if you believe that not much changed in Brazil to alter the aftermath of floods on payment technology in the periods before and after Pix besides Pix itself, you would expect that the effect of floods on other payment methods would be similar in both periods had Pix not been created. Therefore, the growth in the usage of a payment method after a flood would be caused by the increase in the number of users of Pix. Second, we use floods as an instrument for the increase in the number of users of Pix. The main assumption, in this case, is the exclusion restriction: floods will not affect the use of other payment methods directly. This assumption is impossible to test and it would require the reader to believe blindly in it; however, since we have data from before Pix existed, our staggered differences-in-differences act as a reasonable test to see whether this assumption is plausible.

For this task, we direct your eyes to the estimates in black in Figure (4). The estimates in black are the results of Equation (1) on the log transactions of Bank Wire, Payment Slip, and the log number of firms accepting Credit and Debit payments (we do not have transaction-level data on card payments and the number of firms accepting card transactions is defined by having a positive amount of total value transacted that week). The period we studied to create these estimates is from January 2019 until November 2020, when Pix was created. What we find is that, with the exception of highly noisy debit card data, we see no evidence of a systematic change in behavior toward payment methods after a flood.

Alternatively, in the estimates in red of Figure (4), we show the results of the same equation but for the period after Pix was introduced, from November 2020 until December 2022. We find that the usage of other payment methods is systematically affected by floods after Pix. We show that during the period near the natural disaster, estimates are flat, but there seems to be a growth in the use of those payment methods after several weeks. This growth is shown in all alternative methods and this delayed increase is consistent with the idea that once familiarized with Pix, people and firms gradually learn to use other payment methods over time.

In the IV approach, we display in Table (1) the results of the same variables shown in Figure (4). We find consistent results with a 1% increase in the number of active users of Pix in a municipality leading to an increase of 5.7% in the number of Payment Slip transactions and 4.5% in the number of Bank Wire transactions. We also find that the number of firms accepting debit card increases significantly by about 1.2% while credit card acceptance does not change significantly.

Due to the richness of the data, we can offer a more detailed analysis of each payment method. For Payment Slips, our results are presented in Figure (9). We study four main variables, log transaction of Payment Slips (already analyzed in the previous paragraphs), Log Value (the sum of all money transacted), and Log Active Users for people and firms (constructed as the number of unique people and firms that sent or received money using Payment Slips). As seen before, the variables show a similar pattern. The before Pix estimates in black seem to be flat, while the after Pix estimates in red show a modest positive effect of floods on the usage of Payment Slips over time. Running the IV approach on those variables, we find that a 1% increase in the number of active users of Pix in a municipality leads to a 10.7% increase in the value transacted using Payment Slips, a 1.7% increase in the number of active firms, and an insignificant change in people actively using it.

For Bank Wire transfers, refer to Figure (10). As before, we found no evidence of floods affecting Bank Wire before Pix was created. In the period after Pix, in red, we start to see an increase in the usage of Wire only after several weeks. We see a clear increase in the number of transactions and total value transacted. This is consistent with people and firms learning how to use the technology after Pix over time. The pattern in the figure is reflected in the results of the IV approach. We find a growth of 4.5% in the number of transactions and 7.0% in the value transacted, while we do not see a significant change in the number of firms using Wire to receive or send money.

For Credit and Debit card payments, we refer to Figure (11). This data is not as rich as the other payment methods, we only have the total value transacted in a day to each firm, from where we create a dummy to determine whether a firm accepted card payments that week. The estimates for them are a little more erratic than the other payment methods with a lot of noise, but there seems to be no effect of floods on the number of firms accepting credit and debit cards, and the total value transacted before Pix. In the period after Pix, we see a similar partner from before, a delayed increase in the number of firms accepting credit and debit cards, and the total value transacted. In the IV approach, we find a 1.2% increase in the number of firms accepting debit cards, while we do not find a significant effect on the total value transacted of debit and credit cards, nor on the number of firms accepting credit cards.

	Dependent variable:				
	OLS	IV			
	Log Pix Users	Log Trans. Wire	Log Trans. Slip	Log Credit Acceptance	Log Debit Acceptance
	(1)	(2)	(3)	(4)	(5)
Flood	0.022***				
	(0.006)				
Log Pix Users		4.538***	5.737**	−0.132	1.182***
		(1.109)	(2.922)	(0.285)	(0.371)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	614,163	614,163	614,163	614,163	614,163
R^2	0.995	0.853	0.874	0.994	0.991
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1

Overall, we see a similar pattern for all payment methods, no effect of floods on the usage of payment methods before Pix, and a delayed increase in the usage of payment methods after Pix.

Figure 4

This is consistent with the idea that people and firms learn how to use Pix first and then gradually learn how to use other payment methods. The graphs also increase our confidence that flood can be a valid instrument in our analysis. With that, our IV approach points to the fact that the increase in the number of users of Pix is causing an increase in the usage of other payment methods. This result is in contrast to the more natural idea that Pix would substitute other payment methods; instead, we find that Pix is complementary to other payment methods.

5.3 Effects of Pix on Banking

Now we move on to analyze the impact of Pix in the banking sector. There is growing fear that free instantaneous transfer technologies have the potential to disrupt the banking sector. We will analyze a few variables to see if those concerns have any merit.

Similarly to before, we selected some relevant variables to study the effect of Pix on it. We direct the reader to the estimates in black in Figure (5) which are the results of Equation (1) on the (1) log number of people creating a credit relationship for the first time, (2) log number of people creating a relationship with a new bank for the first time, and (3) the log number of people opening bank accounts for the first time. The period we studied to create these estimates is from

January 2019 until November 2020, when Pix was created. The first two variables are calculated on a monthly time frame, while the third is calculated weekly. In the estimates, we see no evidence of a systematic change in behavior toward creating new credit relationships or new bank accounts after a flood.

Alternatively, the estimates highlighted in red in Figure (5) delineate the outcomes of the same equation for the post-Pix implementation period, spanning from November 2020 to December 2022. We find a few positive estimates weeks after the flood for all three variables. Those results are reflected in the IV approach in Table (2) where we find that a 1% increase in the number of active users of Pix in a municipality leads to an increase of 0.45% in the number of people creating a credit relationship, a 0.25% increase in the number of people creating a relationship with a new bank, and a 0.80% increase in the number of people opening bank accounts for the first time.

Due to the richness of the data, we can offer a more detailed analysis of the impact of Pix in the banking sector. First, we explore the impact of Pix on the opening of bank accounts, particularly how this was influenced by a flood both before and after Pix's implementation. In Figure (12) we show the results of the staggered differences-in-differences on the log number of bank accounts for people and firms, the log number of people with at least one bank account in a municipality (log banked population), and the log number of people opening bank accounts for the first time (log adoption). According to the figures, the log adoption of bank accounts before Pix was not affected by floods, while after Pix, we see a few positive estimates weeks after the flood. A similar pattern occurs for the log banked population, as you can imagine since both variables are closely related. The log number of bank accounts for people and firms are very similar and face the same problem since most of the estimates violate the pre-trend assumption despite our fixed effects. The only one that is well-behaved is the log number of bank accounts for firms that rise over time following a flood. Since we face some problems with the pre-trend assumption, the results of the IV approach should be taken with a grain of salt. The results can be viewed in Table (6), where we find that a 1% increase in the number of active users of Pix in a municipality leads to an increase of 0.80% in the number of people opening bank accounts for the first time, a 0.08% increase in the number of people with at least one bank account, an insignificant increase in the number of bank accounts for firms, and a 0.5% increase in the number of bank accounts among individuals.

Second, we study credit relationships between people and firms with their banks. We study three variables, the log number of credit adoption defined as the first time a person or firm creates a credit relationship, the log bank adoption defined as the first time a person or firm creates a relationship with a new bank, and log debt defined as the total amount owed by a person or firm. The results for people are presented in Figure (13), and for firms in Figure (14). There we find very stable graphs showing no evidence that floods affect credit relationships before Pix. After Pix, we also see stable graphs with a few positive estimates during certain months after the flood. The results of the IV approach can be found in Table (7) and Table (8). We find that a 1% increase in the number of active users of Pix in a municipality leads to an increase of 0.45% in the number of people creating a credit relationship and a 0.25% increase in the number of people creating a relationship with a new bank. We did not find evidence of a change in the total debt carried by individuals, also, none of the variables for firms were significant.

Third, we use data from Pix to study two interesting variables, the number of active bank accounts and the number of self-transfers. We define the former variable as the number of bank accounts that were used to send or receive money in a given week, and the latter as a transfer from one individual's bank account to the same individual in another account. The goal is to address the possible issue of people and firms creating bank accounts but not using them and to see whether people and firms are optimizing their use of bank accounts by utilizing Pix to transfer money between them. To study the number of active accounts, refer to Figure (16). We find the number of active bank accounts growing more than 4% for people, outpacing the growth in active Pix users by around 3%. For firms, the number of active bank accounts grows approximately the same as active users, at a rate of around 2%. To study self-transfers, refer to Figure (15), where we find that the number of people and firms actively performing self-transactions grows to 4-5% after 52 weeks.

Overall, the results of this section suggest that Pix contributes to the growth in bank accounts, access to credit, and the expansion of bank products among people. We also find that people and firms are actively using more their bank accounts and optimizing their use by performing self-transfers.

	Dependent variable:		
	IV		
	Log Credit Adoption	Log Bank Adoption	Log First Account
	(1)	(2)	(3)
Log Pix Users	0.445***	0.224***	0.798**
	(0.112)	(0.065)	(0.373)
Mun. FE	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*
Observations	138,325	138,325	614,163
R^2	0.878	0.974	0.851
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2

5.4 Extra Results

In this section we will analyze two main topics, the first is the role of informal insurance in the growth in popularity of Pix following a flood, and the second is which type of bank, traditional or digital, was more favored by the growth in popularity of Pix.

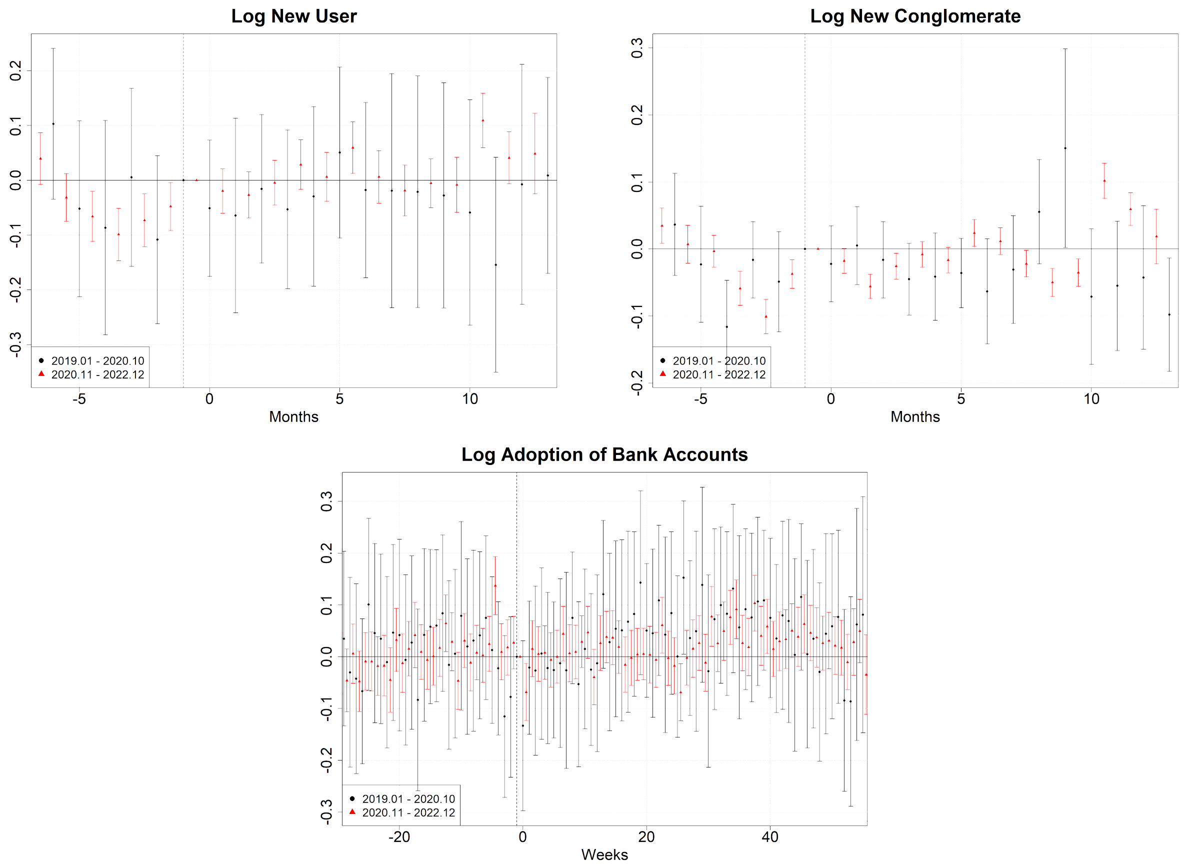


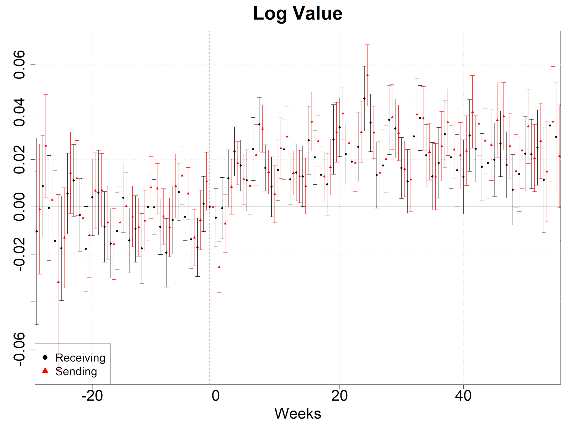
Figure 5

5.4.1 Informal Insurance

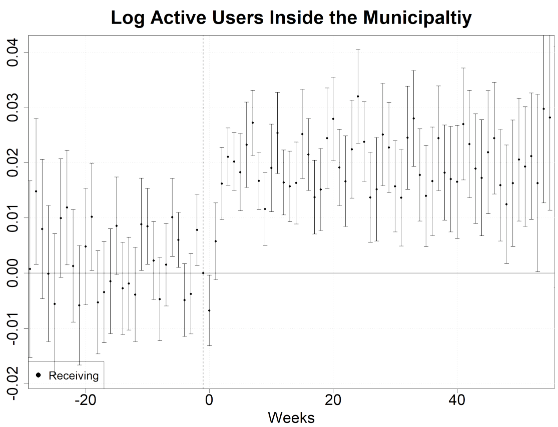
To study informal insurance, we study remittances, which in this case, we define as a transaction of Pix between a person outside the municipality affected by the flood and a person inside the municipality. Moreover, we define as inflow, a transaction from a person outside the municipality to a person inside the municipality, and as outflow, a transaction from a person inside the municipality to a person outside the municipality.

The main graphs of our analysis are presented in Figure (6). In the first two graphs, the estimates in black are the results of Equation (1) on the inflow, while the red ones refer to the outflow. We find that in the week of the flood, there is a significant drop in the outflow of money, while the number of inflow transactions increases significantly. This is consistent with informal insurance in which people affected by the flood decrease the outflow while increasing the inflow. The last two graphs show the number of people affected by the flood receiving remittances and the number of people not affected by the flood sending remittances. We find that during the week of the flood, more people outside the municipality send money to people inside the municipality. In all graphs, we see a permanent change in behavior following the flood, with remittances growing around 2-4%, and a network effect of Pix, with people outside the municipality increasing their use of Pix to send money.

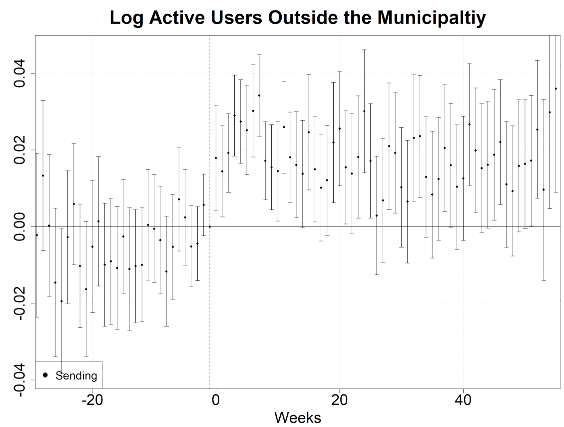
(a) Log Remittances



(b) Log Value Remitted



(c) Receivers of Remittances



(d) Senders of Remittances

Figure 6

5.4.2 Heterogeneous analysis

In this section, we study the effects of Pix on different types of banks. Since there is a common sense belief that digital banks and fintechs would take over traditional brick-and-mortar banks, we divide banks into two categories, digital banks and traditional banks based on their physical branch presence.

First, we study Pix transactions using Equation (1) on the log number of transactions and the total value of Pix for people and firms between those different banks. The results are presented in Figure (18), the estimates in black represent the traditional banks, while in red, the digital banks. We find that for people, the growth in Pix transactions and the total value transacted are almost identical. Thus, indicating that both types of banks were favored similarly after a flood. Alternatively, for firms the results seem to differ, despite the high noise and pre-trend violation, the estimates show that traditional banks grew more in the number of transactions and total value transacted. This is on par with the idea that firms benefit much more from traditional banks since they can offer better services and credit.

Second, we look at the number and active use of bank accounts. The results are presented in Figure (19). Regarding the number of bank accounts, we face the same problem as before with some violations to the pre-trend assumption in the case of people. In the case of firms, the estimates are more well behaved, with the growth in digital accounts appearing to be bigger than traditional accounts following a flood, but the results are not significant. The result is on par with firms having established relationships with traditional banks, decreasing potential growth in new bank accounts. While for new digital banks, it is natural to experience bigger growth in accounts. Concerning active usage, a pattern consistent with previous observations emerges. Individuals' active usage of bank accounts increases at comparable rates for both digital and traditional banks, with estimates adhering to the pre-trend assumption. On the other hand, firms demonstrate a greater increase in active use of traditional bank accounts. However, the estimates do not comply with the pre-trend assumption.

Overall, we find evidence that for people, both types of banks were favored similarly by the growth in popularity of Pix, while for firms, our evidence is of worse quality, but it seems to indicate that traditional banks have been more favored by the growth in popularity of Pix.

6 Robustness

Our empirical identification relies on the exclusion restriction assumption. To increase the validity of this assumption, we study the periods "Before Pix", from January 2019 until November 2020. The idea is that if floods did not affect our main variables before Pix, then it is reasonable to believe that floods would not affect them in the period after Pix, except through Pix. One may argue that studying results from January 2019 until November 2020 as our "placebo" period does not capture fully the effect of Covid and it is possible that our results are driven by the change in behavior caused by Covid. To check on the possibility that Covid was the main driver of our results, we study the period "Before Pix" from March 2020 until November 2020, and the period "After Pix" from November 2020 until June 2021.

The same results from Section (8.2) in the Appendix are reproduced in Section (8.4). The results are very similar, with even stronger results of floods affecting the use of Pix and Pix affecting our main payment and banking variables. The results are naturally noisier given the loss of observations. However, the main conclusion remains the same: floods do not have a significant effect on our main variables before Pix and Covid does not seem to be the driver of change, Pix does.

7 Conclusion

In conclusion, this paper studies an important aspect of the evolving financial landscape, the development of transfer technologies. Although previous studies have shed light on the positive impact of these transfer systems, the speed of development and popularization of these technologies remain slow worldwide compared to Pix (see figure 7). One of the reasons for this reluctance is the fear that these technologies could compete with existing payment technologies and possibly disrupt the banking sector. At the same time, innovation on the payment technology front, such as Pix, has the potential to substitute for cash transactions, pushing people and firms toward using more their bank accounts and other financial technologies.

We overcome the challenge of separating the substitutability or complementarity of Pix on other payment methods from changes in consumer preferences, by using floods as an instrument for the increase in the usage of Pix. We find that floods have a significant effect on the usage of Pix, while not having a significant effect on the usage of other payment methods or in our banking variables before Pix, thus clearing the way for an Instrumental Variable approach.

We discover that floods have a lasting impact on the usage of Pix, with a significant increase in the number of people and firms using Pix even after one year. We also find evidence that Pix is used for informal insurance, with a significant increase in the inflow of money from people outside the municipality and in the number of people sending and receiving remittances. We also find that the use of Pix by firms is also affected after a flood, with a significant increase in the number of firms accepting Pix as a payment method.

When studying the effects of Pix on other payment methods, we find evidence that Pix causes significant increases in the four most used payment technologies in Brazil: Payment Slips, Bank Wire, Credit card, and Debit card. We show that following Pix use, people seem to be more open to using other payment methods. Similarly, firms seem to be more open to accepting other payment methods once they start accepting Pix.

In the banking sector, we find that Pix contributes to the growth in bank accounts, access to credit, and expansion of bank products among people. We also find that people and firms are actively using more their bank accounts and that they are optimizing the use of their accounts by performing self-transfers. Regarding which type of bank was favored by the growth in popularity of Pix, we find that traditional and digital banks were favored similarly.

In sum, Pix seems to have brought a financial revolution to Brazil. Since its introduction, access to banking services moved from branches to phones, cash transactions were cut in half, and the whole economy became more digital. In this research, we were able to unveil the effect of Pix on the payment and banking sectors to shed light on the many benefits that instantaneous transfer systems can bring to individuals, firms, and banks. We hope that these findings can encourage the development of new transfer technologies and increase their adoption worldwide.

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8 Appendix

8.1 Graphs

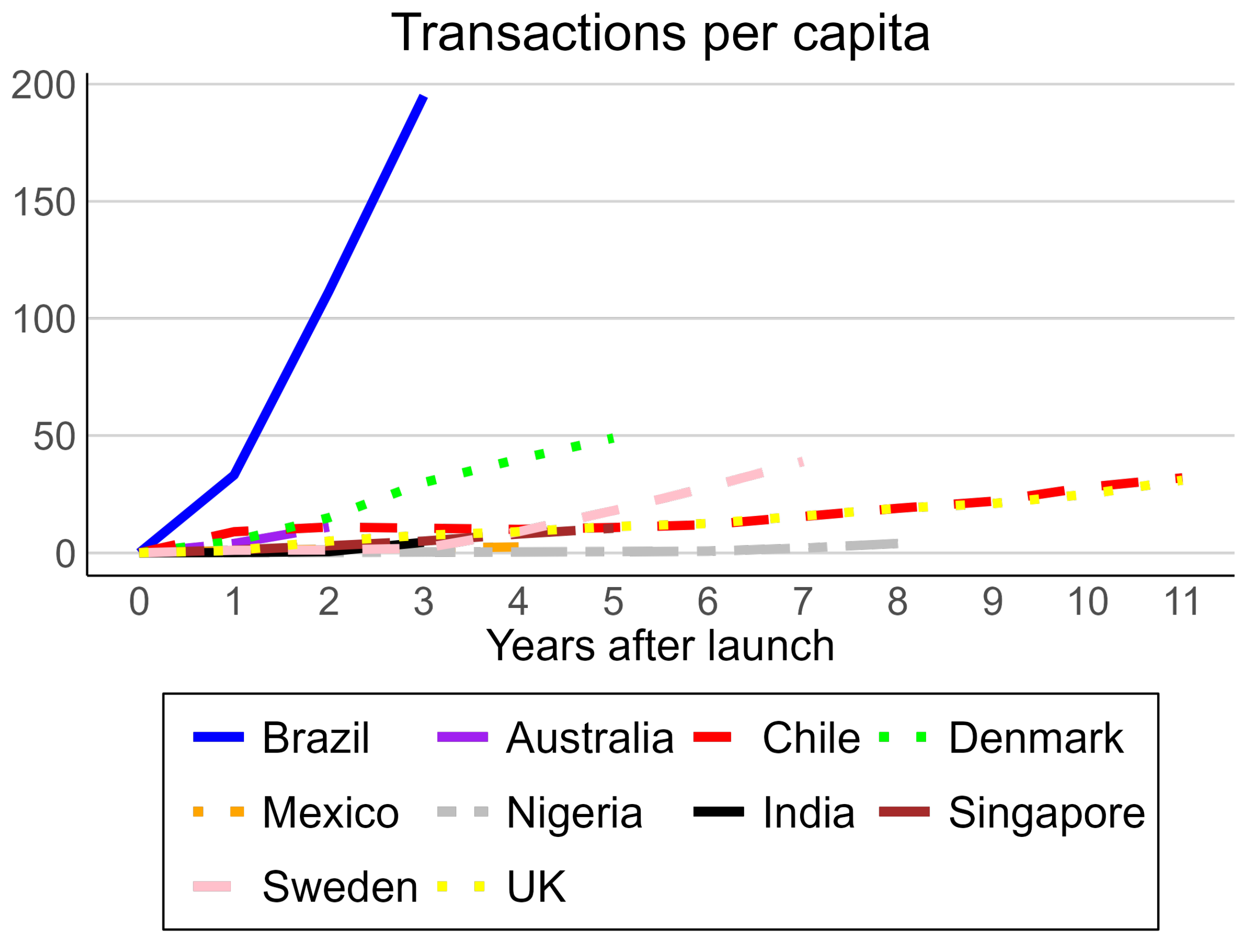
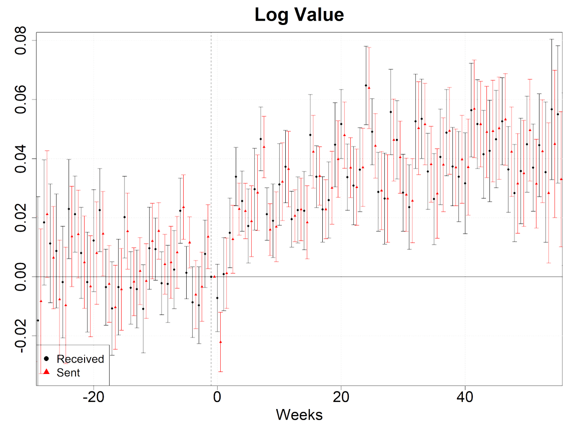


Figure 7: Data from Bech et al. [2020], Duarte et al. [2022], and BCB.

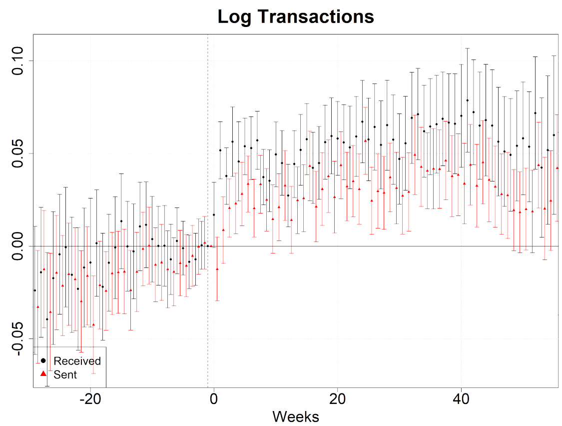
8.2 Expansion of Results

8.2.1 Pix

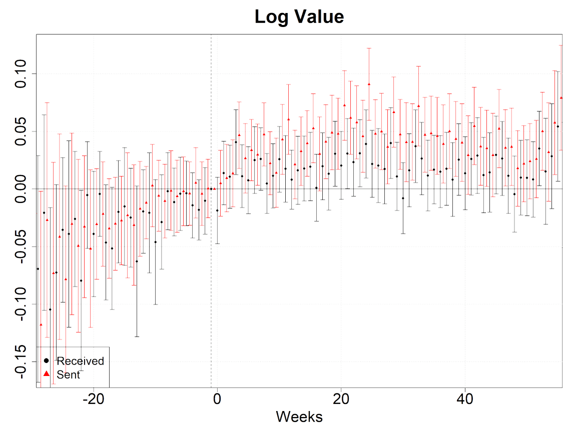
(a) People - Pix



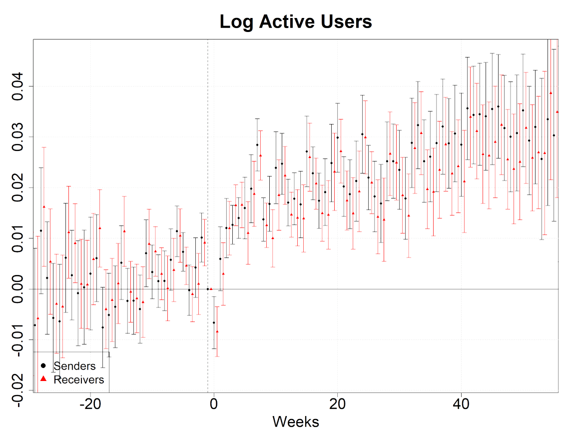
(b) People - Pix



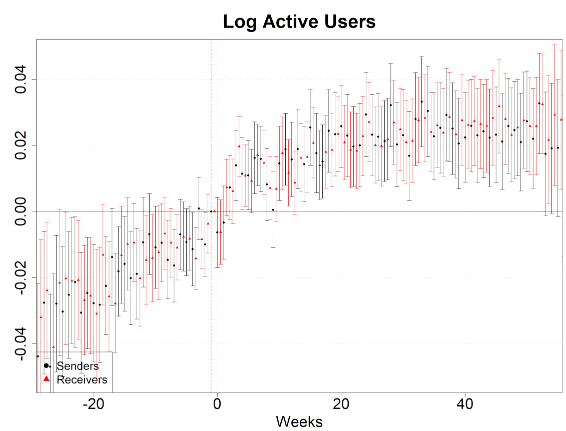
(c) Firms - Pix



(d) Firms - Pix



(e) People - Pix



(f) Firms - Pix

Figure 8: Active User is defined as 1 if that person or firm performed or received any transactions during that week. Transactions are defined as the sum of all transactions received and sent by people or firms. Value is defined as the sum of all values transacted by people or firms.

8.2.2 Payment Slip

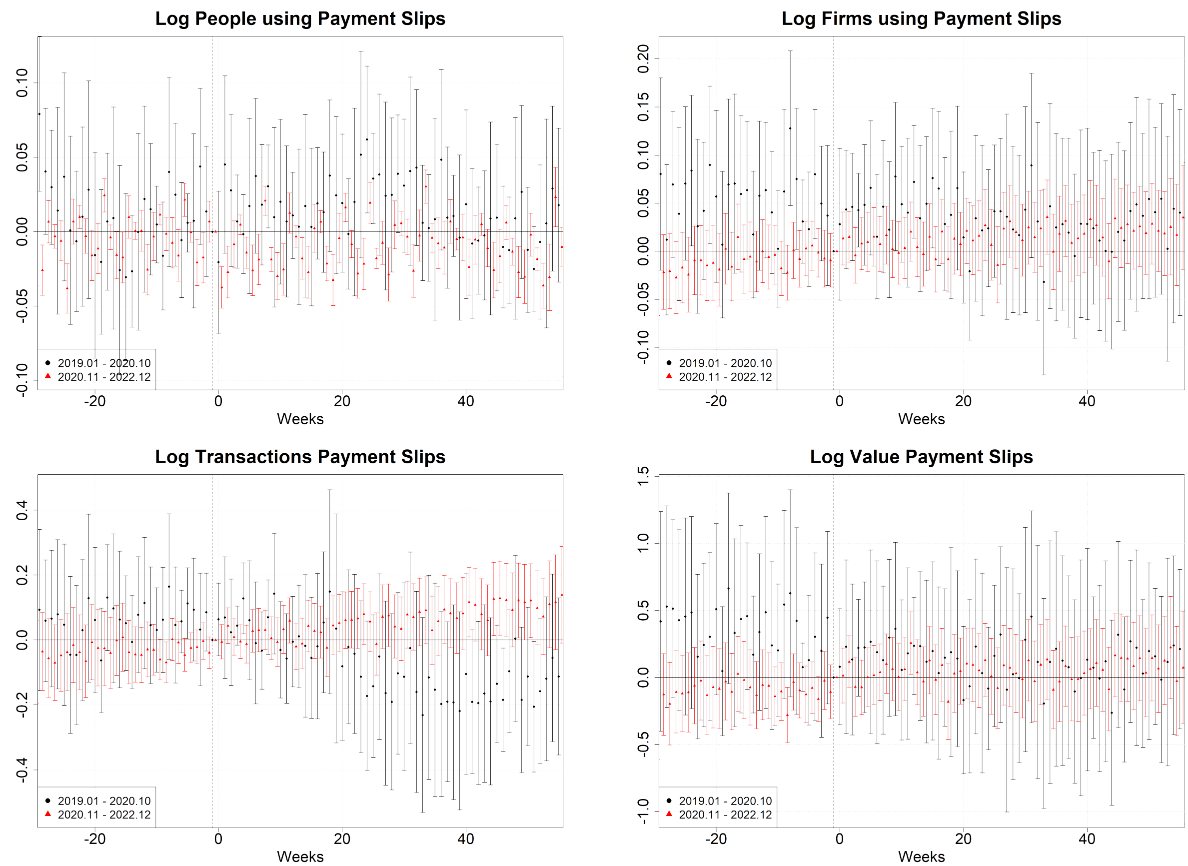


Figure 9

	Dependent variable:				
	OLS		IV		
	Log Pix Users	Log Trans. Slip	Log Value Slip	Log Receivers Slip	Log Senders Slip
	(1)	(2)	(3)	(4)	(5)
Flood	0.022***				
	(0.006)				
Log Pix Users		−0.045	1.664*	5.737**	10.700*
		(0.114)	(0.870)	(2.922)	(6.357)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	614,163	614,163	614,163	614,163	614,163
R^2	0.995	0.991	0.955	0.874	0.799
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 3

8.2.3 Bank Wire

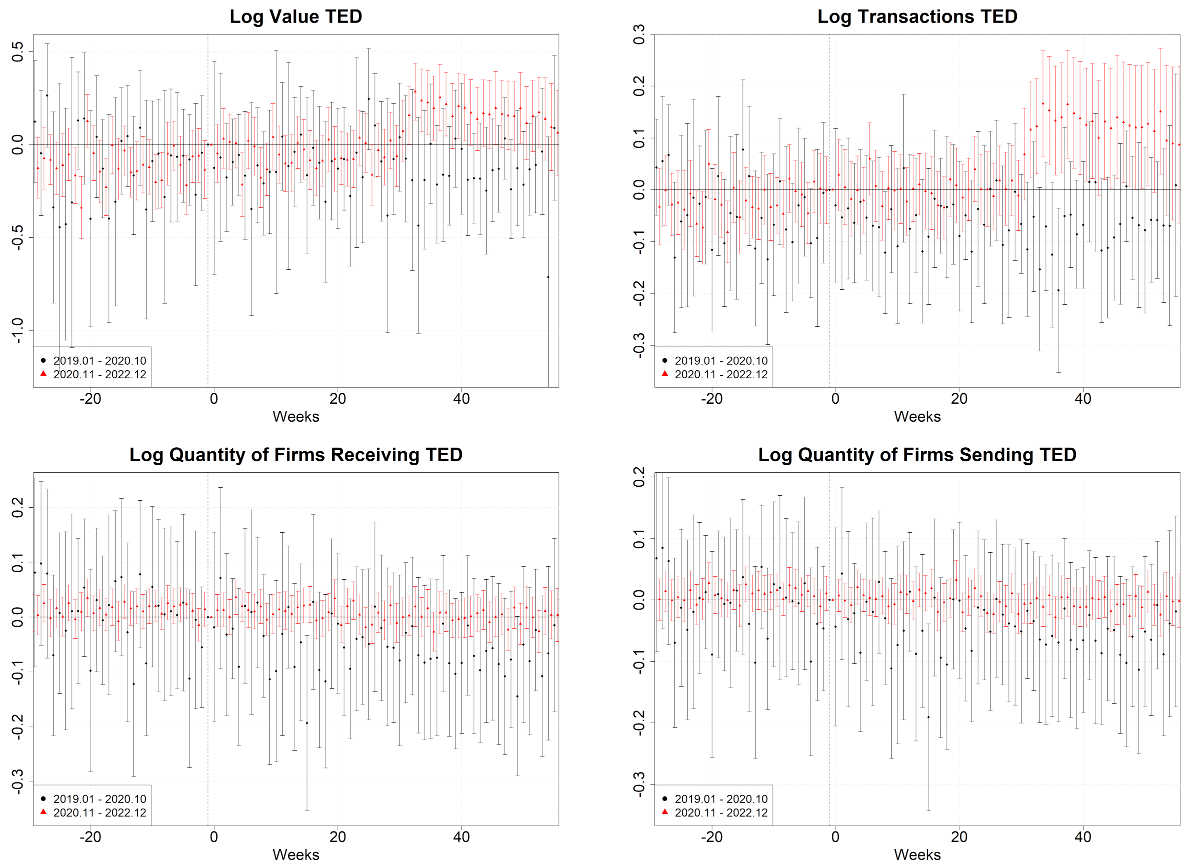


Figure 10: Bank Wire

	Dependent variable:				
	OLS	IV			
	Log Pix Users	Log Trans. Wire	Log Value Wire	Log Receivers Wire	Log Senders Wire
	(1)	(2)	(3)	(4)	(5)
Flood	0.023***				
	(0.006)				
Log Pix Users		7.047***	4.538***	−0.049	−0.144
		(1.946)	(1.109)	(0.369)	(0.369)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	605,875	614,163	614,163	605,875	605,875
R^2	0.995	0.923	0.853	0.951	0.952
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 4

8.2.4 Card Payments

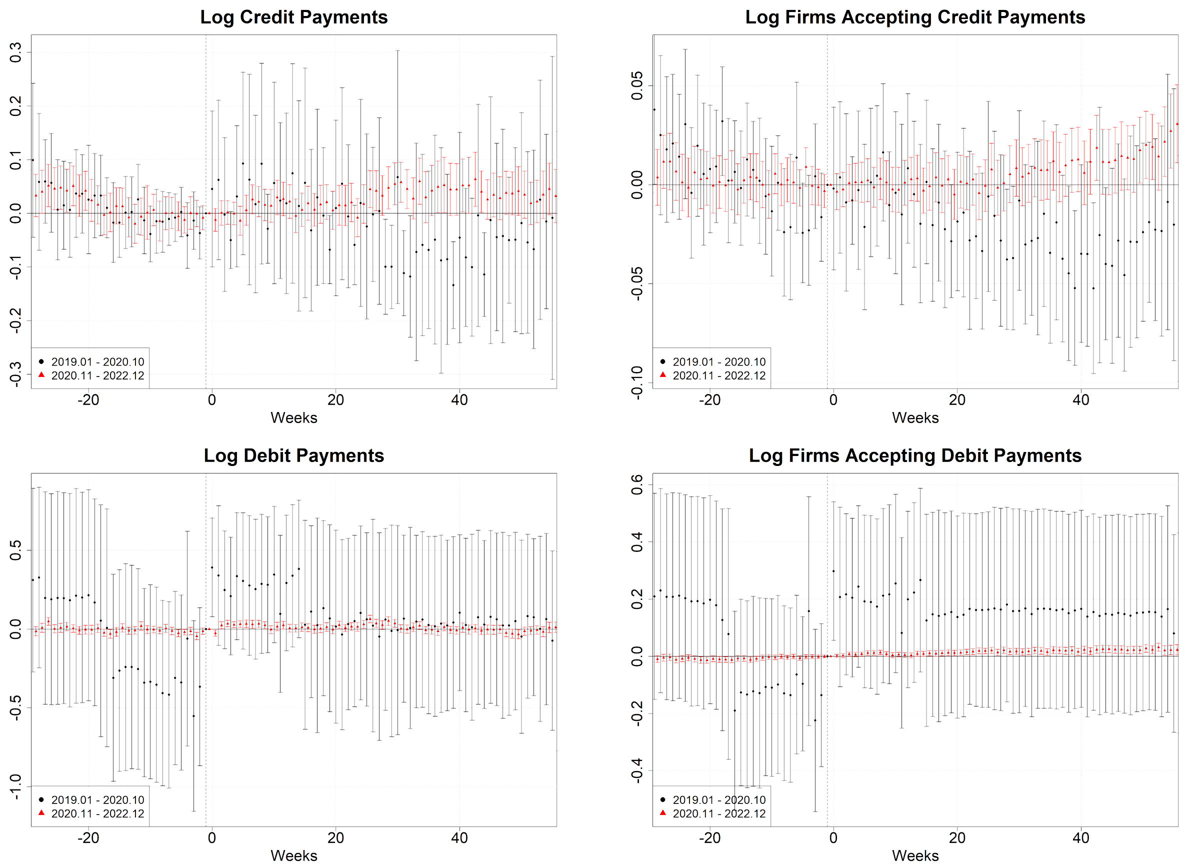
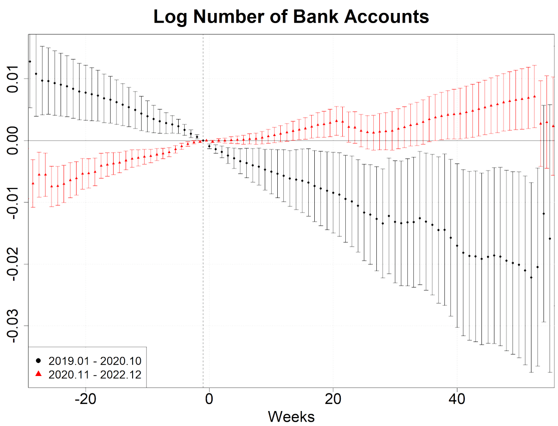


Figure 11

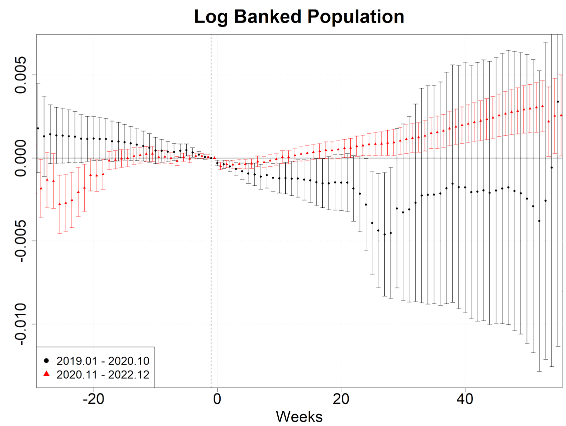
	Dependent variable:				
	OLS	IV			
	Log Pix Users	Log Value Credit	Log Credit Acceptance	Log Value Debit	Log Debit Acceptance
	(1)	(2)	(3)	(4)	(5)
Flood	0.022***				
	(0.006)				
Log Pix Users		−0.132	0.109	1.182***	0.225
		(0.285)	(0.612)	(0.371)	(0.400)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	614,163	614,163	614,163	614,163	614,163
R^2	0.995	0.994	0.973	0.991	0.983
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5

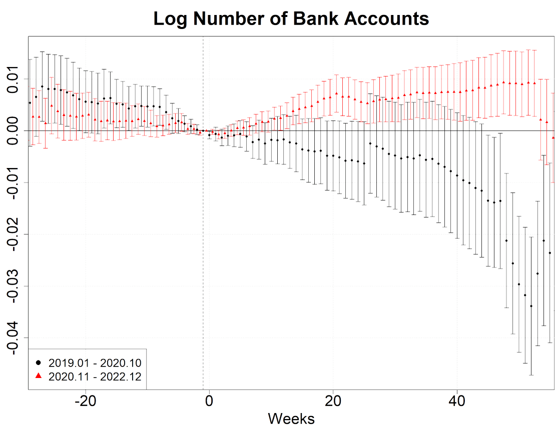
8.2.5 Bank Accounts



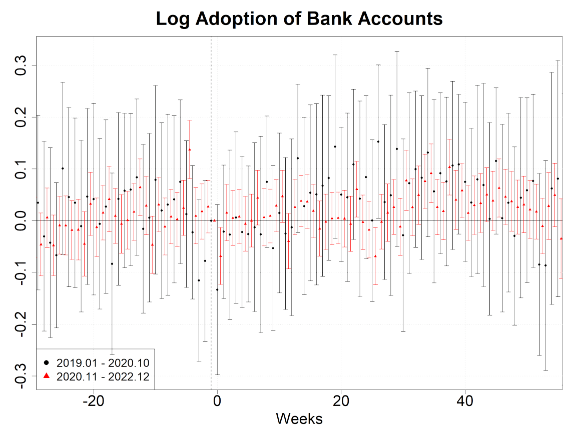
(a) Log number of Bank Accounts - People



(b) Log number of People with Bank Accounts



(c) Log number of Bank Accounts - Firms



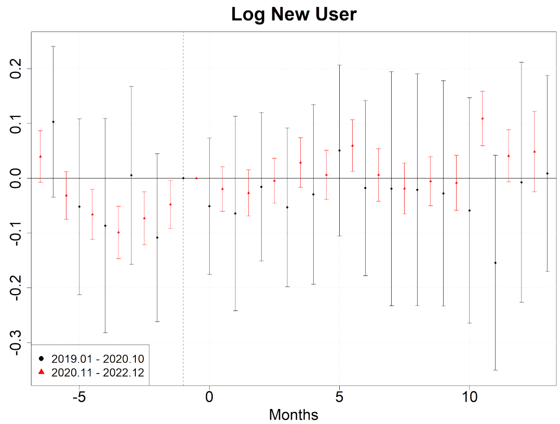
(d) Log Adoption of Bank Accounts

Figure 12

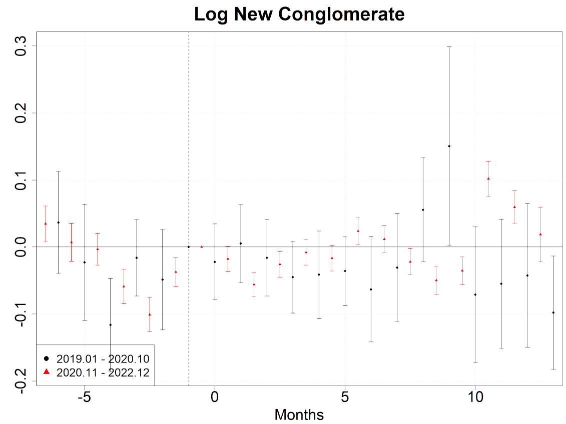
	Dependent variable:				
	OLS	IV			
	Log Pix Users	Log Bank Accounts - People	Log Banked Population	Log First Account	Log Bank Accounts - Firms
	(1)	(2)	(3)	(4)	(5)
Flood	0.022***				
	(0.006)				
Log Pix Users		0.514***	0.081**	0.798**	0.047
		(0.194)	(0.035)	(0.373)	(0.149)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	614,163	614,163	614,163	614,163	614,163
R^2	0.995	0.998	1.000	0.851	0.999
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 6

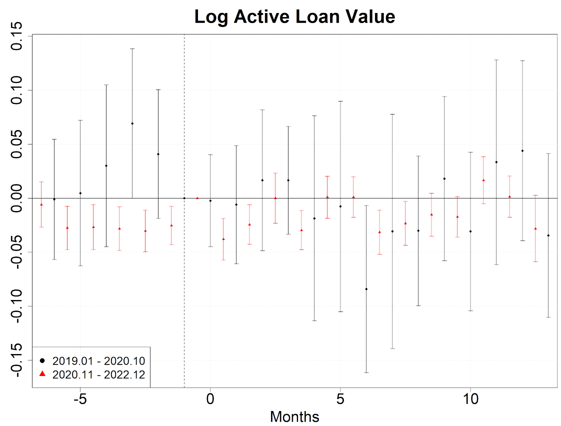
8.2.6 Credit Relationships



(a) Log New Users



(b) Log New Conglomerate

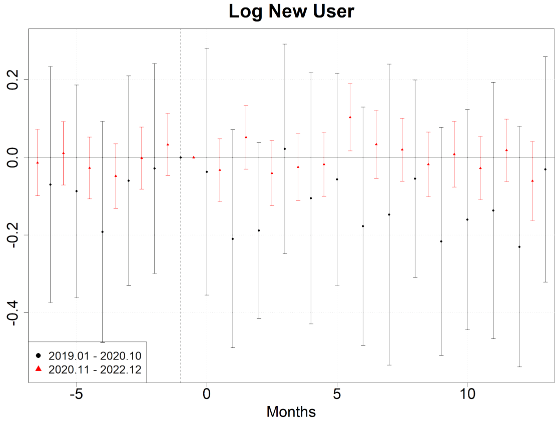


(c) Log Active Loan Value

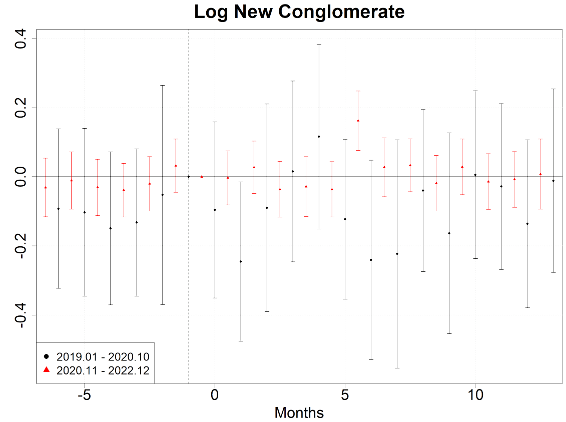
Figure 13: Credit

	Dependent variable:			
	OLS	IV		
	Log Pix Users	Log Credit Adoption - People	Log Bank Adoption - People	Log Debt - People
	(1)	(2)	(3)	(4)
Flood	0.118***			
	(0.025)			
Log Pix Users		0.445***	0.224***	0.038
		(0.112)	(0.065)	(0.037)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	138,325	138,325	138,325	138,325
R^2	0.995	0.878	0.974	0.984
Note:				*p<0.1; **p<0.05; ***p<0.01

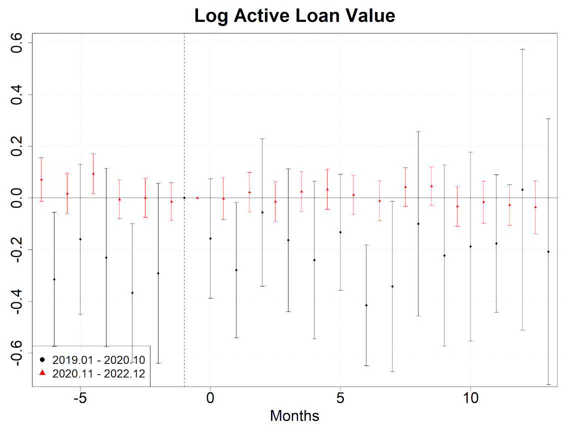
Table 7



(a) Log New Users



(b) Log New Conglomerate



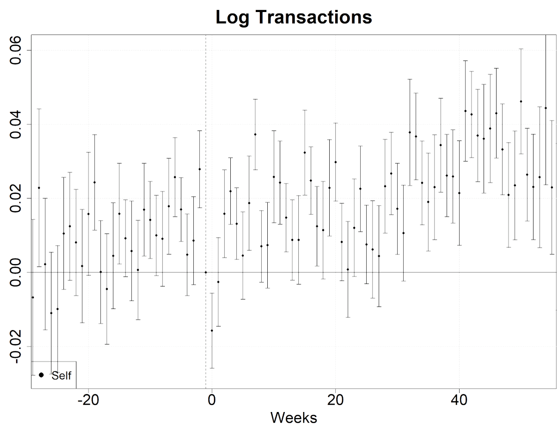
(c) Log Active Loan Value

Figure 14: Credit

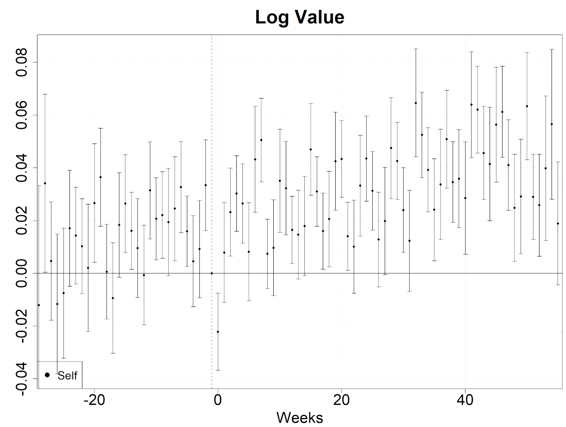
	Dependent variable:			
	OLS	IV		
	Log Pix Users	Log Credit Adoption - Firms	Log Bank Adoption - Firms	Log Debt - Firms
	(1)	(2)	(3)	(4)
Flood	0.118***			
	(0.025)			
Log Pix Users		0.020	0.182	−0.267
		(0.114)	(0.128)	(0.175)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	138,325	138,325	138,325	138,325
R^2	0.995	0.793	0.833	0.885
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8

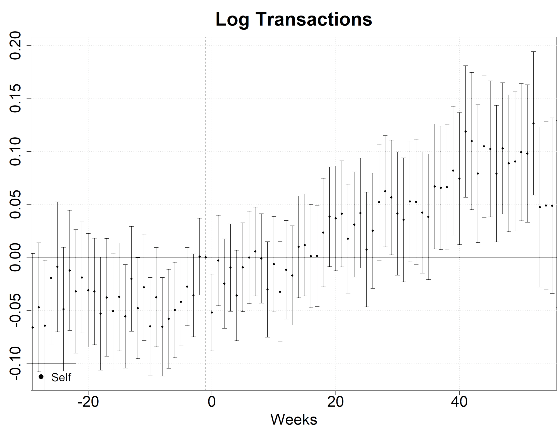
8.2.7 Self Transactions



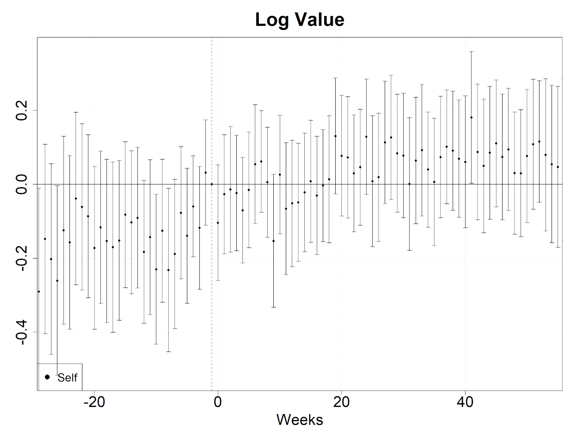
(a) Log Transactions



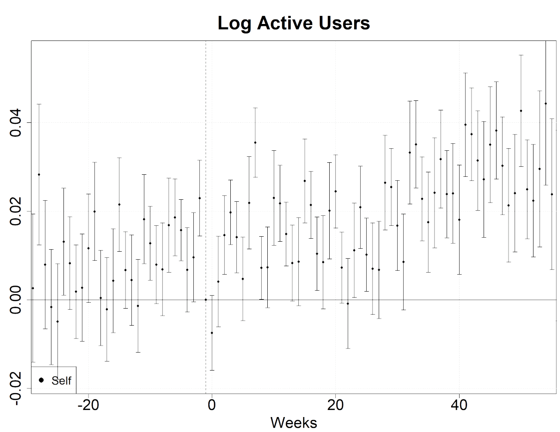
(b) Log Value



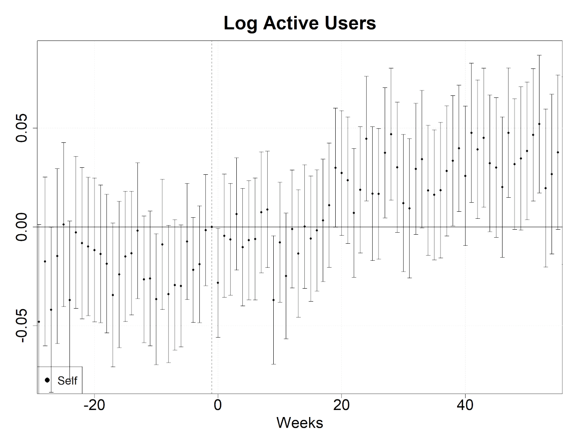
(c) Log Transactions



(d) Log Value



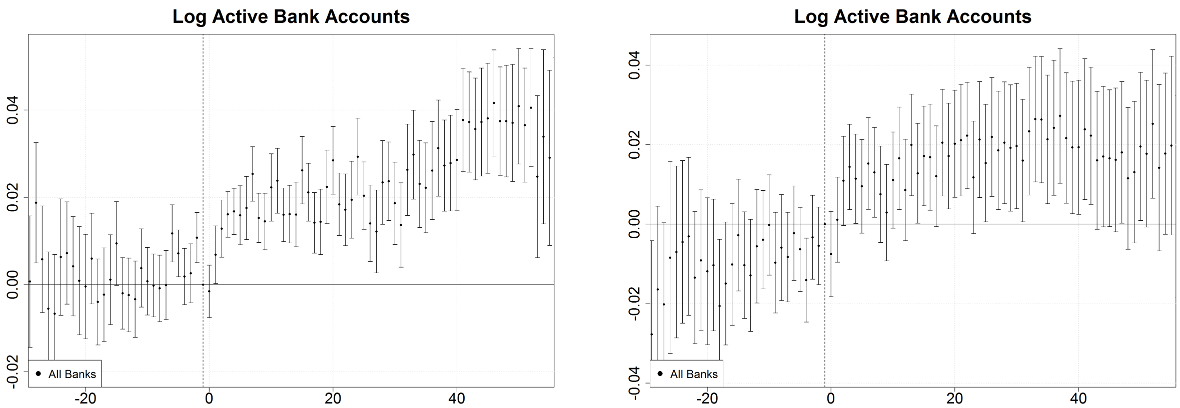
(e) Log Active Users



(f) Log number of Receivers

Figure 15: Self

8.2.8 Active Accounts



(a) People

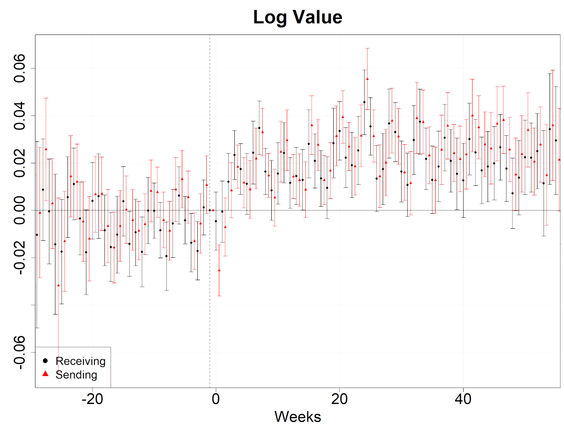
(b) Firms

Figure 16

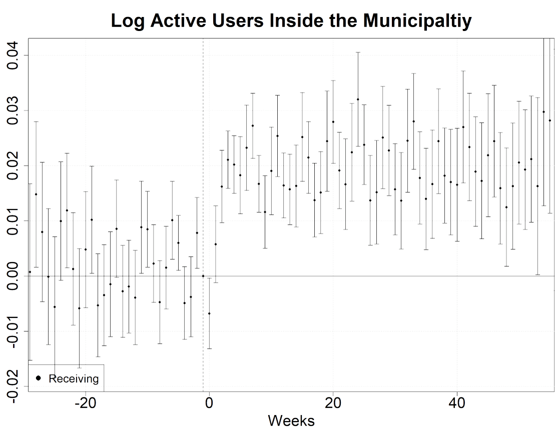
8.3 Other Results

8.3.1 Informal Insurance

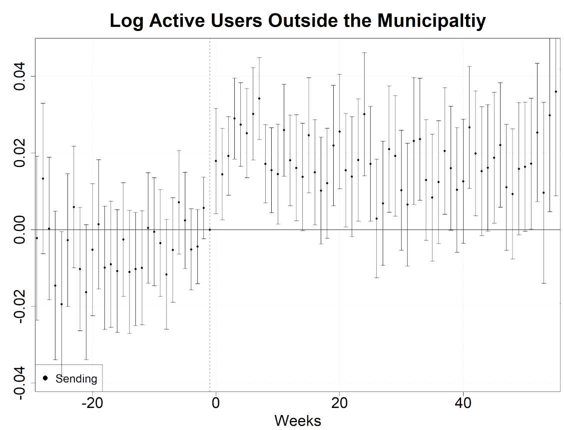
(a) Log Remittances



(b) Log Value Remitted



(c) Receivers of Remittances



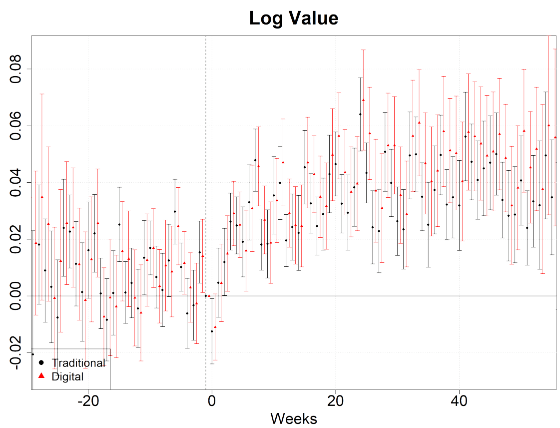
(d) Senders of Remittances

Figure 17

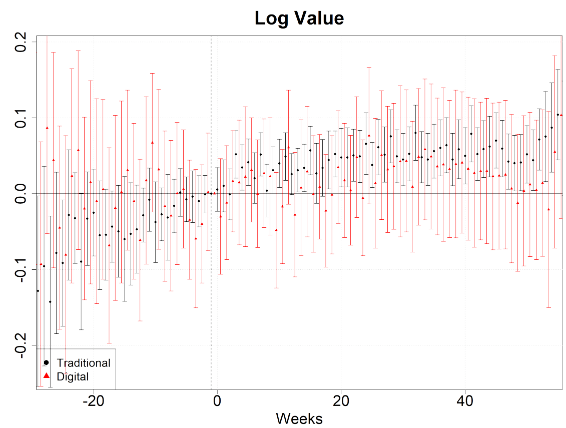
8.3.2 Heterogeneous Analysis

(a) People

(b) Firms

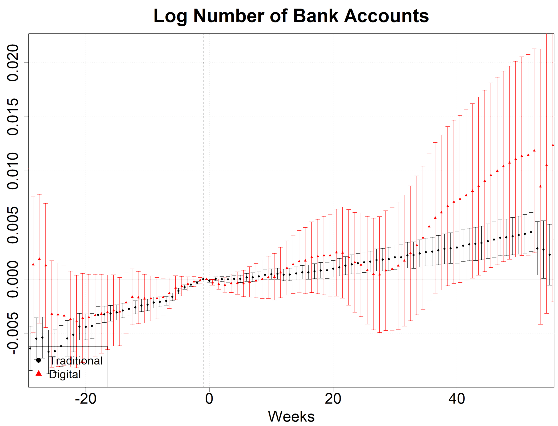


(c) People

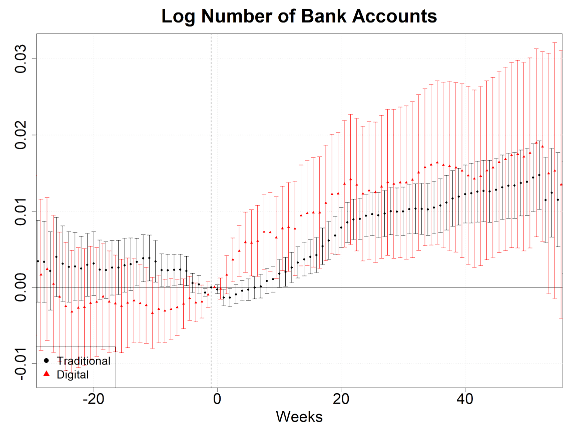


(d) Firms

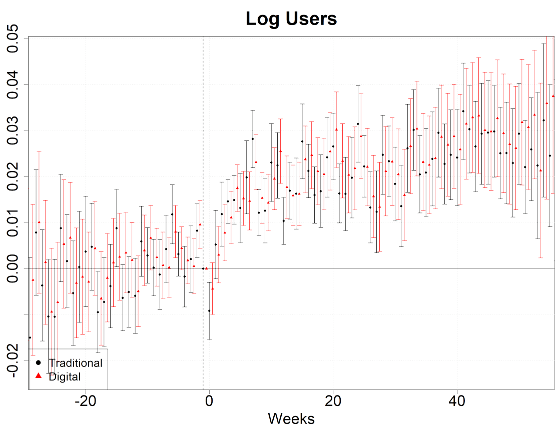
Figure 18



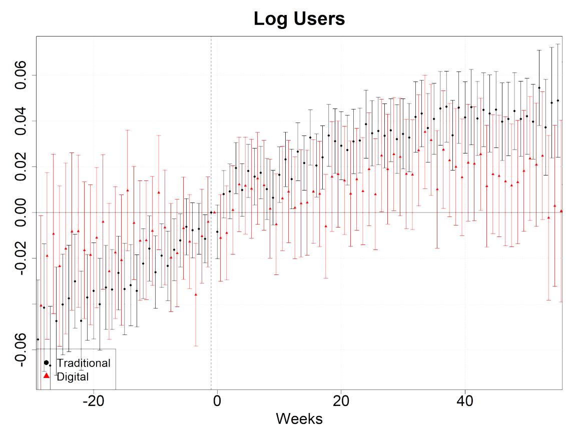
(a) People



(b) Firms



(c) People

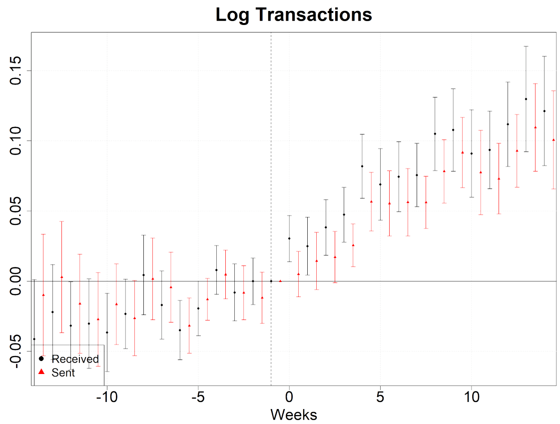


(d) Firms

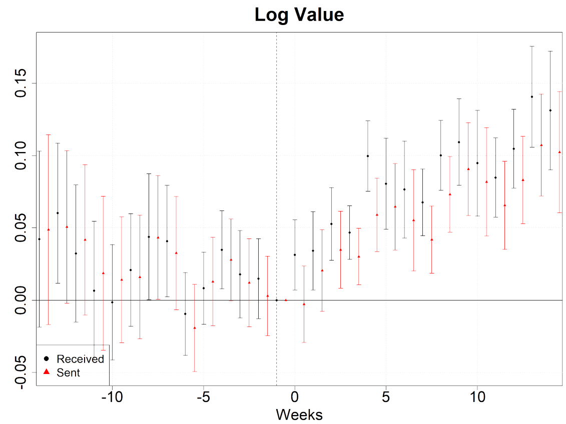
Figure 19

8.4 Robustness

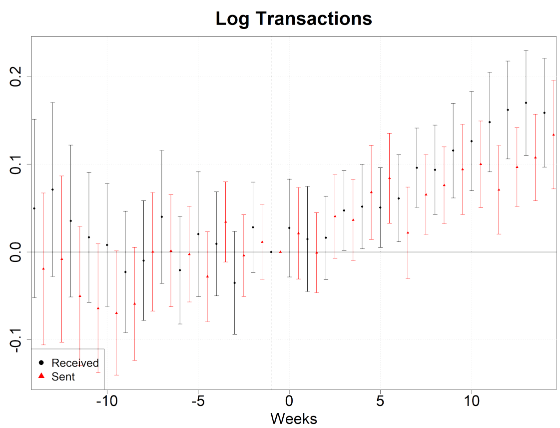
8.4.1 Pix



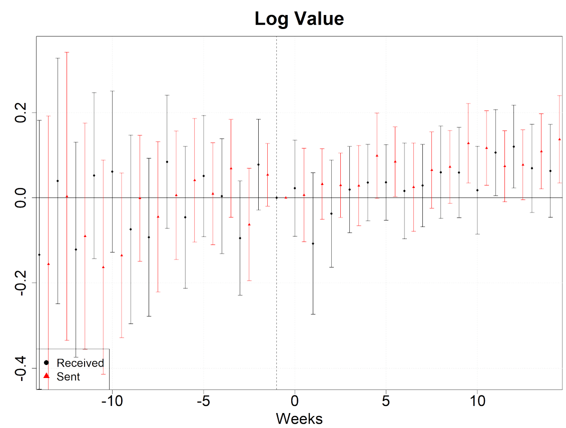
(a) People - Pix



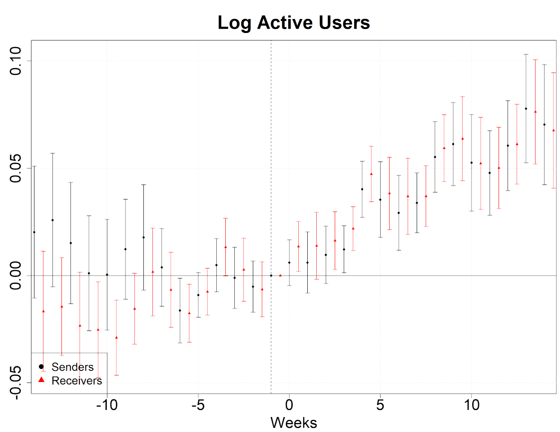
(b) People - Pix



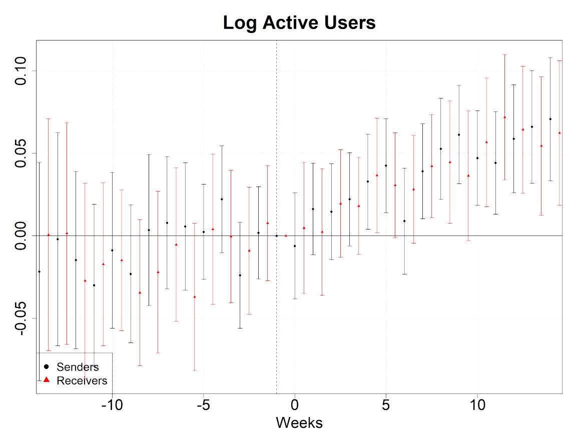
(c) Firms - Pix



(d) Firms - Pix



(e) People - Pix



(f) Firms - Pix

Figure 20: Active User is defined as 1 if that person or firm performed or received any transactions during that week. Transactions are defined as the sum of all transactions received and sent by people or firms. Value is defined as the sum of all values transacted by people or firms.

8.4.2 Payment Slip

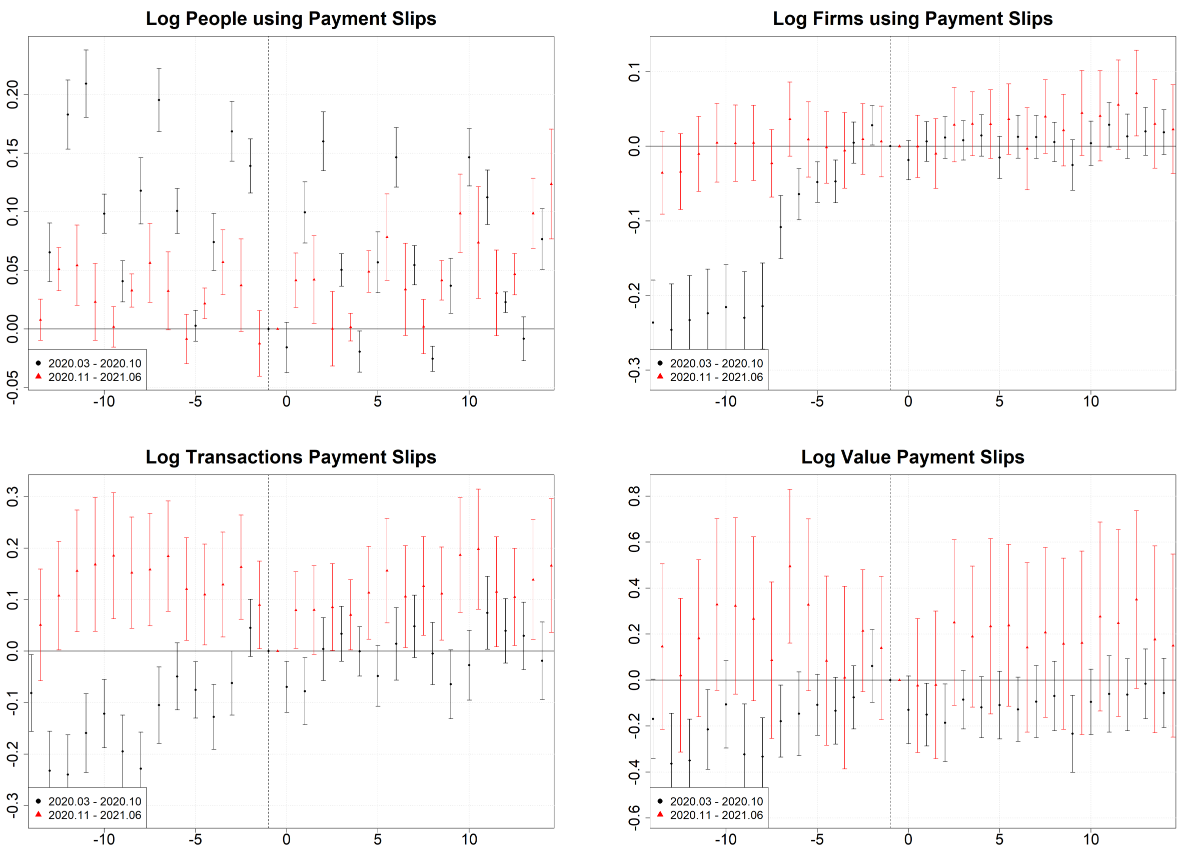


Figure 21

	Dependent variable:				
	OLS	IV			
	Log Pix Users	Log Trans. Slip	Log Value Slip	Log Receivers Slip	Log Senders Slip
	(1)	(2)	(3)	(4)	(5)
Flood	0.034***				
	(0.009)				
Log Pix Users		0.882***	0.852	0.142	0.185
		(0.273)	(0.580)	(1.407)	(3.481)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	204,721	204,721	204,721	204,721	204,721
R^2	0.996	0.991	0.980	0.972	0.917
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 9

8.4.3 Bank Wire

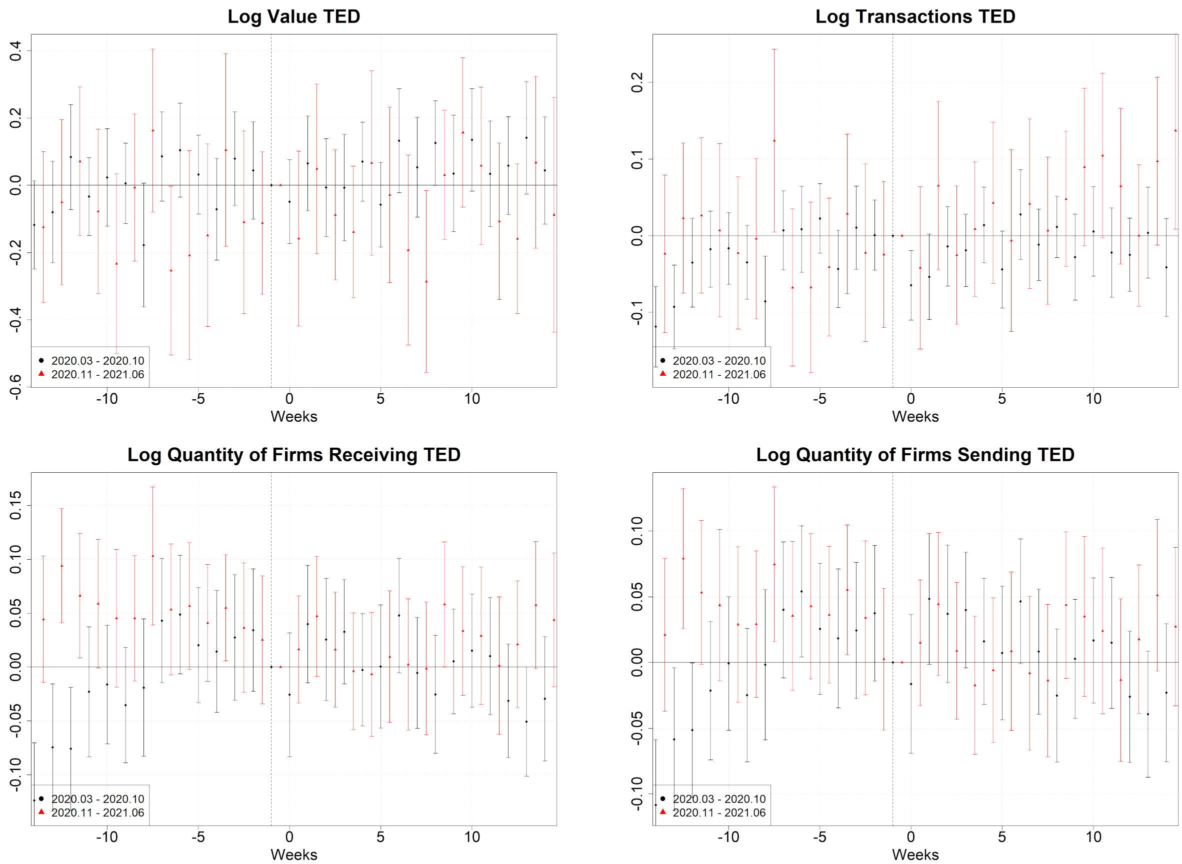


Figure 22: TED

	Dependent variable:				
	OLS	IV			
	Log Pix Users	Log Trans. Wire	Log Value Wire	Log Receivers Wire	Log Senders Wire
	(1)	(2)	(3)	(4)	(5)
Flood	0.034***				
	(0.009)				
Log Pix Users		1.323	1.501***	−0.990**	−0.773**
		(0.983)	(0.579)	(0.431)	(0.385)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	201,705	204,721	204,721	201,705	201,705
R^2	0.996	0.753	0.907	0.954	0.956
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 10

8.4.4 Card Payments

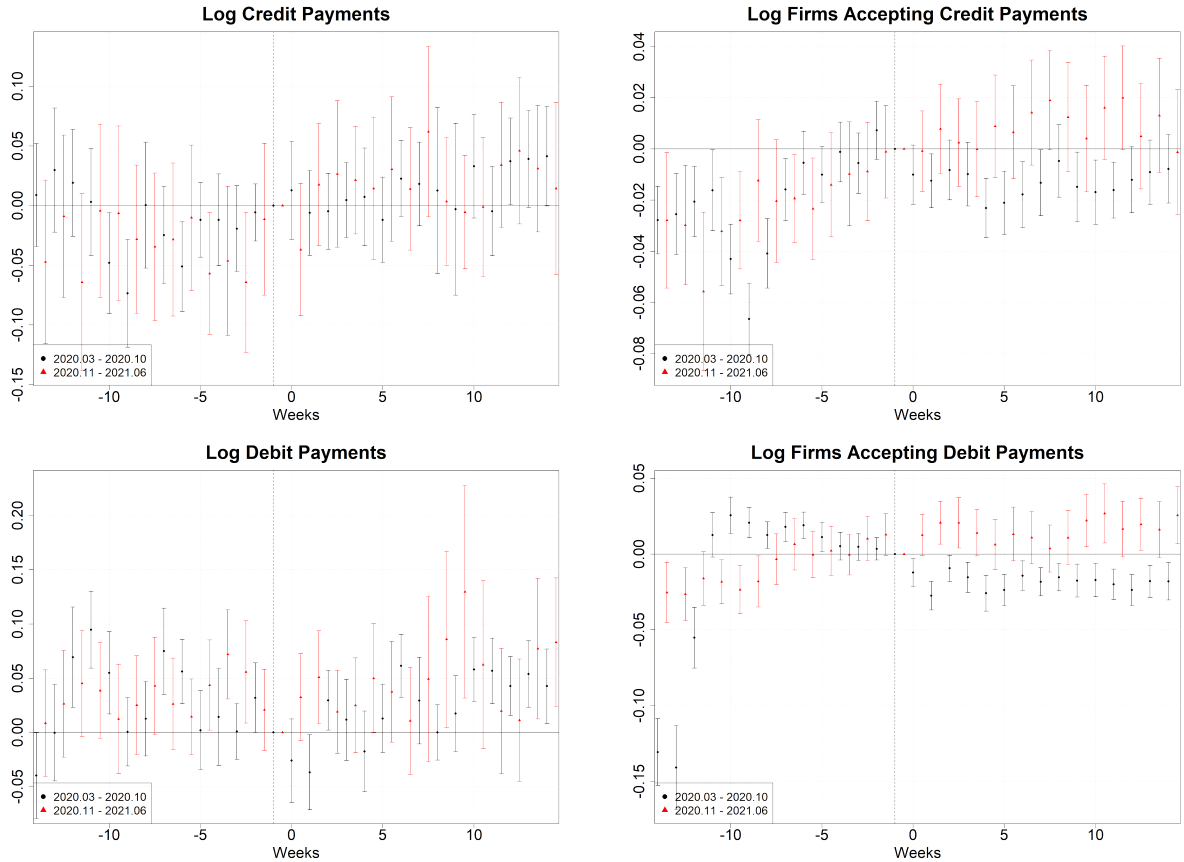
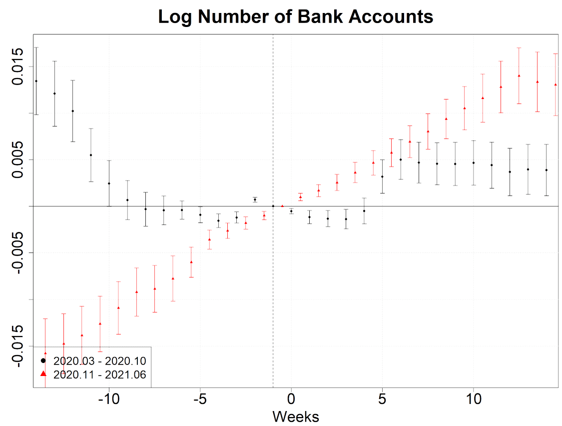


Figure 23

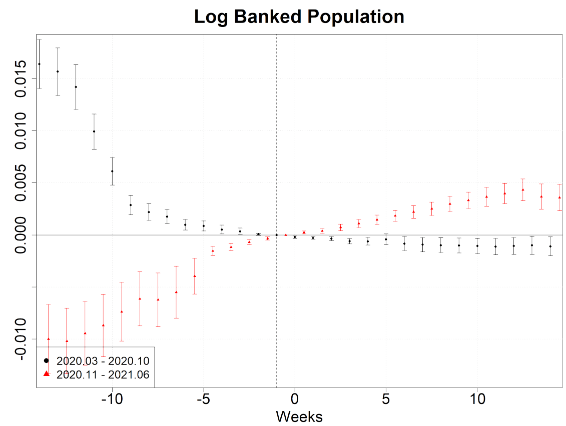
	Dependent variable:				
	OLS	IV			
	Log Pix Users	Log Value Credit	Log Credit Acceptance	Log Value Debit	Log Debit Acceptance
	(1)	(2)	(3)	(4)	(5)
Flood	0.034***				
	(0.009)				
Log Pix Users		0.886***	1.733***	0.768***	0.676*
		(0.282)	(0.609)	(0.214)	(0.397)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	204,721	204,721	204,721	204,721	204,721
R^2	0.996	0.994	0.979	0.996	0.987
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 11

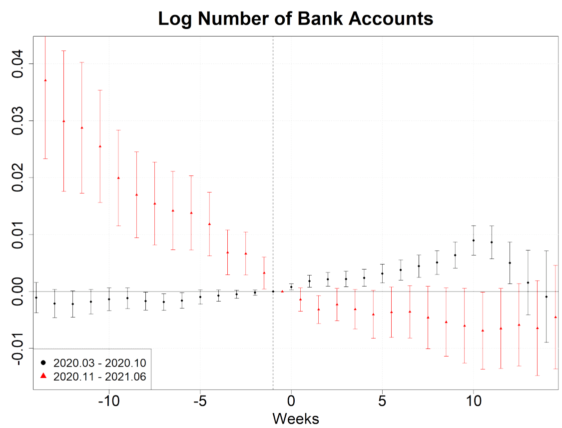
8.4.5 Bank Accounts



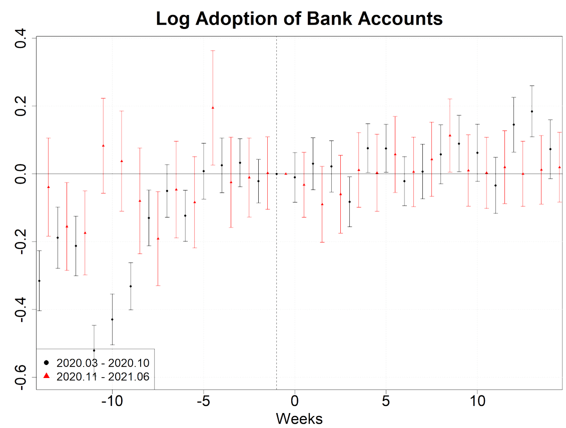
(a) Log number of Bank Accounts - People



(b) Log number of People with Bank Accounts



(c) Log number of Bank Accounts - Firms



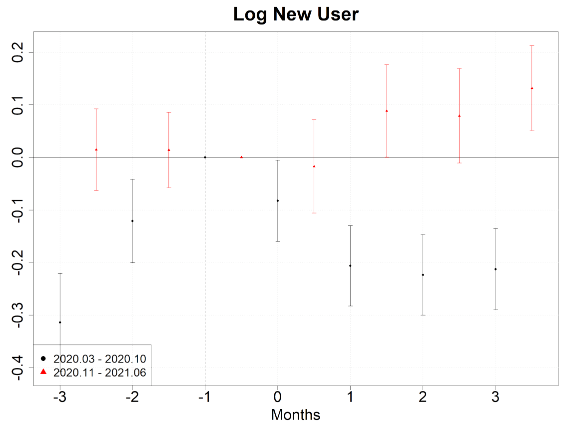
(d) Log Adoption of Bank Accounts

Figure 24

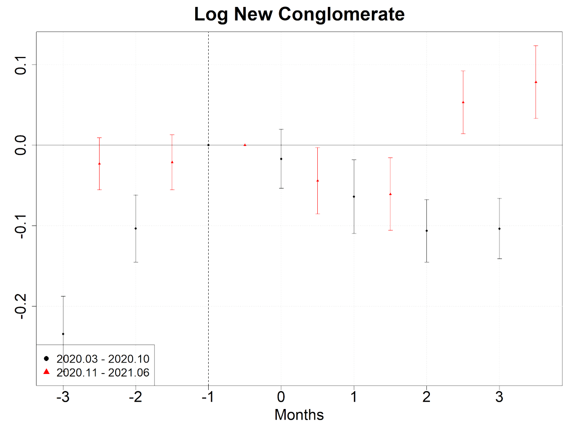
	Dependent variable:				
	OLS	IV			
	Log Pix Users	Log Bank Accounts - People	Log Banked Population	Log First Account	Log Bank Accounts - Firms
	(1)	(2)	(3)	(4)	(5)
Flood	0.034***				
	(0.009)				
Log Pix Users		0.590***	0.321***	1.628**	−0.767***
		(0.152)	(0.083)	(0.768)	(0.219)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	204,721	204,721	204,721	204,721	204,721
R^2	0.996	0.998	0.999	0.803	0.997
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 12

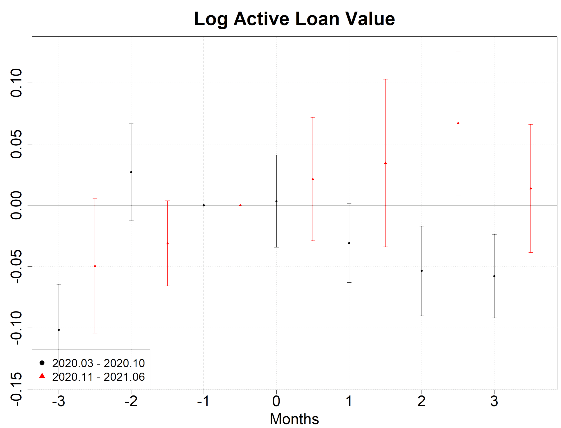
8.4.6 Credit Relationships



(a) Log New Users



(b) Log New Conglomerate

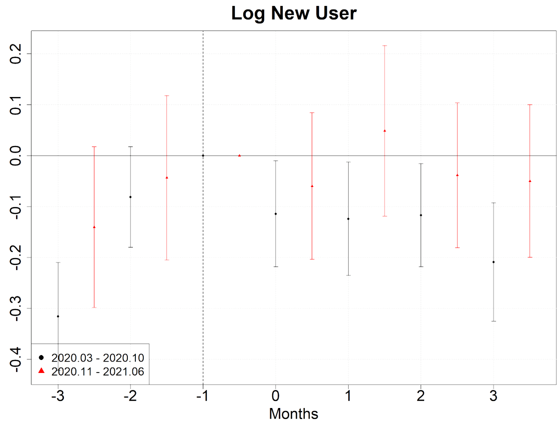


(c) Log Active Loan Value

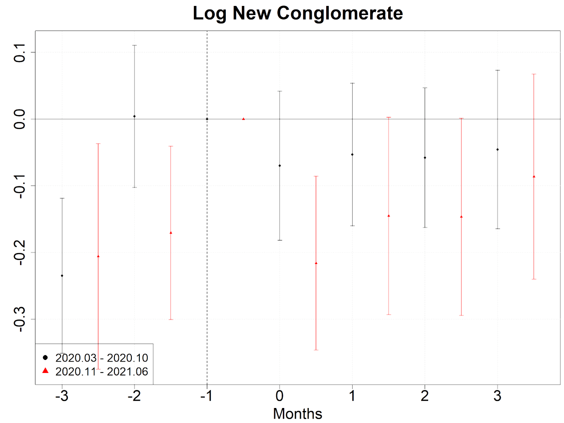
Figure 25: Credit

	Dependent variable:			
	OLS	IV		
	Log Pix Users	Log Credit Adoption - People	Log Bank Adoption - People	Log Debt - People
	(1)	(2)	(3)	(4)
Flood	0.009			
	(0.062)			
Log Pix Users		6.111	3.201	7.494
		(41.670)	(21.695)	(50.783)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	44,264	44,264	44,264	44,264
R^2	0.993	-13.936	-2.482	-17.698
Note:				*p<0.1; **p<0.05; ***p<0.01

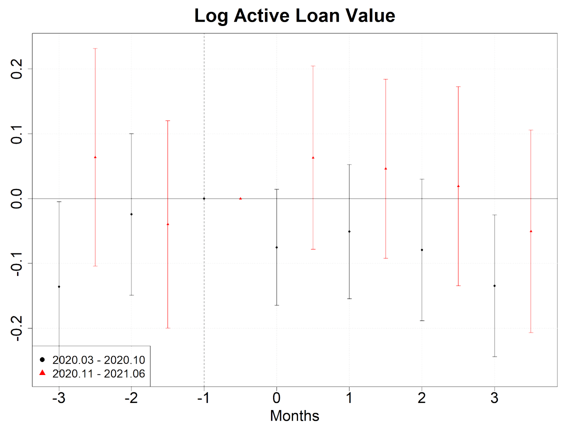
Table 13



(a) Log New Users



(b) Log New Conglomerate



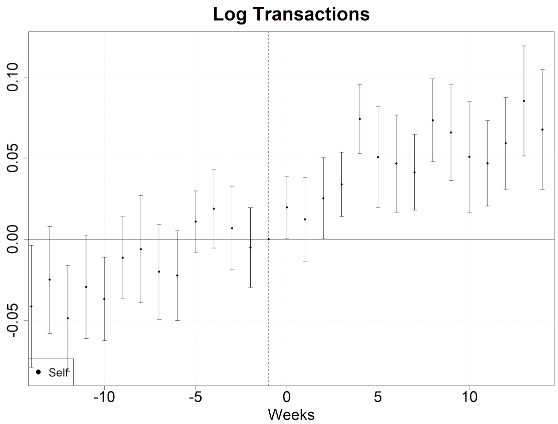
(c) Log Active Loan Value

Figure 26: Credit

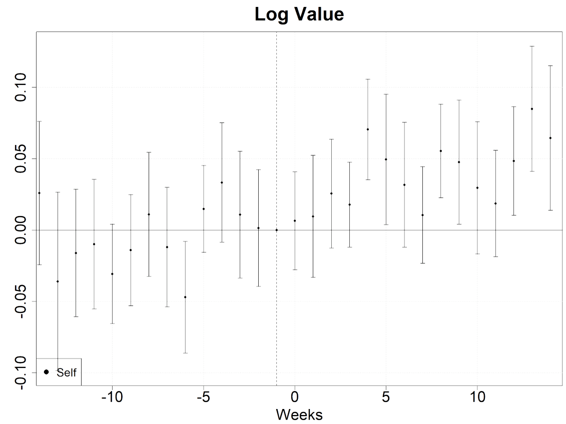
	Dependent variable:			
	OLS	IV		
	Log Pix Users	Log Credit Adoption - Firms	Log Bank Adoption - Firms	Log Debt - Firms
	(1)	(2)	(3)	(4)
Flood	0.009			
	(0.062)			
Log Pix Users		3.798	−3.621	2.609
		(26.317)	(25.011)	(18.199)
Mun. FE	*Yes*	*Yes*	*Yes*	*Yes*
Time x Region FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	44,264	44,264	44,264	44,264
R^2	0.993	-5.746	-3.402	0.195
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 14

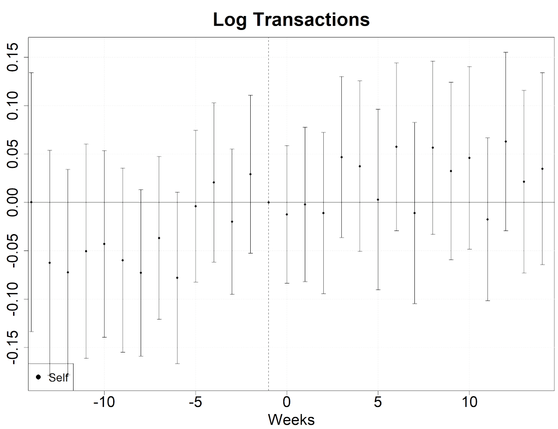
8.4.7 Self Transactions



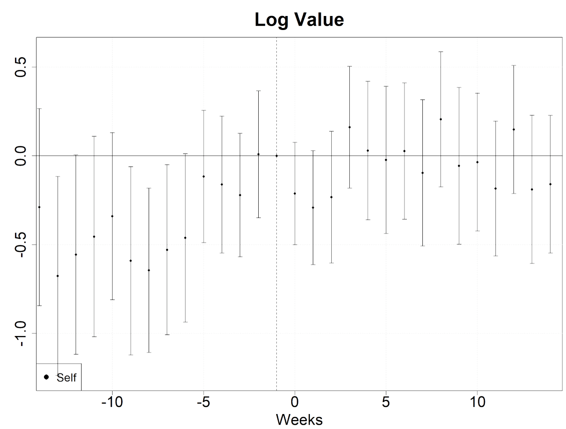
(a) Log Transactions



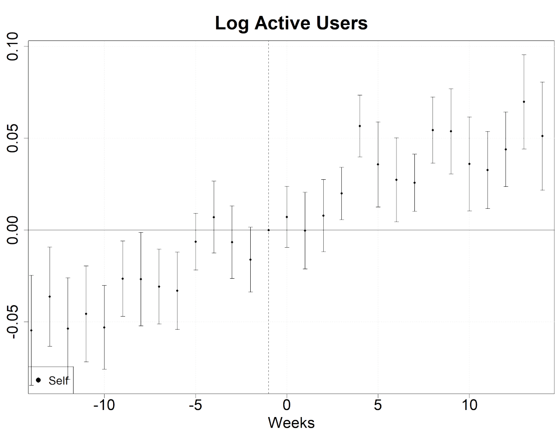
(b) Log Value



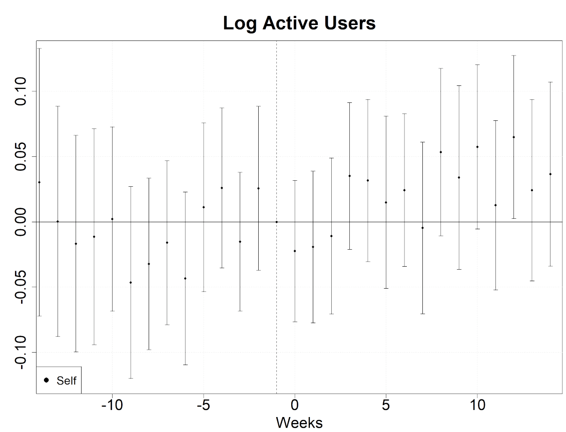
(c) Log Transactions



(d) Log Value



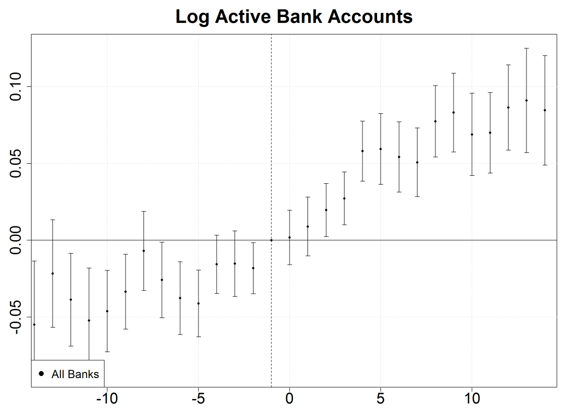
(e) Log Active Users



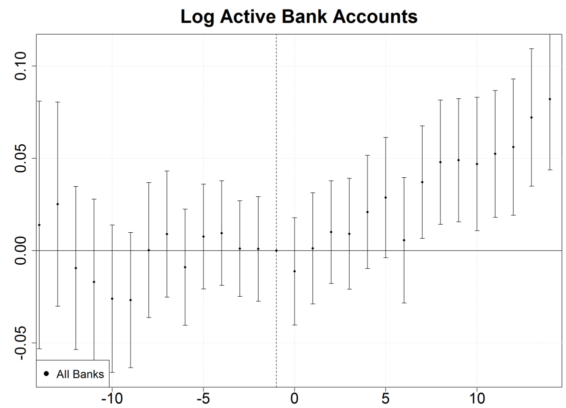
(f) Log number of Receivers

Figure 27: Self

8.4.8 Active Accounts



(a) People



(b) Firms

Figure 28