Utrecht University | School of Economics

Master Thesis U.S.E.

Central Bank Instant Payment Systems and its Impact on Bank Performance and Financial Stability: Evidence from Brazil

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June 28th, 2024

Abstract

The present thesis explores the rise of Pix, an innovative instant payment system developed by the Central Bank of Brazil, and its potential shocks in the performance and stability of the Brazilian banking system. Using quarterly data from 73 financial institutions during the period of 2020 to 2023, this paper investigates whether the total financial volume and number of transactions conducted through Pix has had a significant impact on the profitability measures, performance transmission mechanisms and individual risk of Brazilian banks. The results indicate that Pix has negatively impacted the profitability of banks, primarily through lowering its fee income and net interest margins. In addition, by investigating the difference responses to Pix between traditional and digital banks, the findings reveal that the profitability of the latter group is significantly more sensitive to increases in Pix's transacted volumes. Furthermore, the individual insolvency risk of both traditional and digital banks is deteriorated by Pix, although the effect for digital banks is considerably more adverse. As FinTechs take the bigger losses, the findings emphasize important differences in the business models of incumbent and digital financial institutions. Finally, it suggests that Pix acts as a new player in the payment market, increasing competition between Brazilian banks and pressuring their net interest margins as they compete for depositors.

Keywords: Instant Payments, Bank Performance, Financial Stability, Competition, Fixed Effects

JEL Codes: G21, G24, E58, C23

Acknowledgements

First and foremost, I would like to express my deepest gratitude to Dr. Mohamad Kaakeh, who I was lucky enough to have as my thesis supervisor. Thank you for the guidance and support you gave me throughout the entire process and for the prompt availability for meeting in feedback sessions, answering my questions and clarifying my doubts.

Second, I would like to thank my family in Brazil that provided me with all the emotional and financial support to conclude this overseas journey. Thank you for trusting in me and for enabling this accomplishment. If it weren't for you, I would never be here.

Third, I express my gratitude to all the professors of the Banking and Finance MSc who shared their knowledge and passion for finance with me. Your teachings have expanded my horizons and will be invaluable to my future. To my fellow colleagues, I wish you all the best for a successful career.

Finally, I'd like to thank my dear housemates who were with me in the brightest and darkest moments of this year. You made this journey unforgettable, and your friendship will be the most valuable asset I take from here.

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List of Abbreviations

ATM	Automated Teller Machine
B2B	Business-to-Business
BCB	Banco Central do Brasil
BIS	Bank of International Settlements
CB	Central Bank
CBDC	Central Bank Digital Currency
CTI	Cost-to-Income
EU	European Union
FI	Financial Institution
GDP	Gross Domestic Product
IPS	Instant Payment System
LLP	Loan Loss Provisions
NIM	Net Interest Margin
P2B	Person-to-Business
P2P	Person-to-Person
POS	Point of Service
PSP	Payment Service Provider
ROA	Return on Assets
ROE	Return on Equity
TPP	Third Party Platform

1. Introduction

The present thesis aims at uncovering the nexus between digital payments and bank accounting and market indicators, focusing on how the performance and risk of banks are affected by the emergence of a state-owned instant payment system (IPS). To answer such question, this research will study the case of Pix, the Central Bank of Brazil's (BCB) IPS, and its impact on Brazilian banks.

The world economy is gradually shifting towards digitalization as innovation in financial services is rapidly developing. Retail payments are in the forefront of this change given the intensity, frequency, and comprehensiveness of its usage. Currently, around 60 countries have implemented fast (or near-instant) retail payment infrastructures, out of which most have direct involvement of their central bank, as they are fundamental in maintaining the soundness of the payment system given their role of operator, catalyst and overseer (BIS, 2020). TARGET Instant Payment Settlement (TIPS) in the eurozone, Cobro Digital (CoDi) in Mexico, Faster Payment System (FPS) in Hong Kong, Unified Payment Interface (UPI) in India, Pix in Brazil and more recently, FedNOW in the US are prominent examples. It is broadly accepted by central banks that the development of safe, reliable, and fast payment systems will boost competition in the financial sector, lower costs for consumers and enhance economic growth (BCB, 2023; BIS, 2020).

In Brazil, the recent evolution of the retail payment landscape is striking, making the country relevant to study the impacts of IPSs. According to a survey conducted by the BCB in 2019, 77% of retail payments in the country were made with cash (BCB, 2021). The report concluded the need to incentivize the digitalisation of the payment system within the country. Pix was officially launched in November 2020 and due to its rapid and intense adoption among Brazilians, in only a few years it has reached remarkable figures: In December 2023, there were over 4.8 billion transactions made via Pix, a nominal growth of over 3,200% since December 2020 (BCB, 2024). The financial volume transacted also increased by over 1,500% in the same period to R$ 1.9 trillion. As of January 2024, a total of 150 million Brazilians had used Pix to either make or receive payments at least one time, accounting for almost 70% of the country's population (BCB, 2024). Moreover, the BCB claimed that by 2022, Pix was responsible to financially include 71.5 million people in the country.

The development of digital, mobile-based, and fast payment methods has triggered great interest among academics in recent years, although the scope of existing research on this topic is quite varied. Most of the research conducted has been concentrated in examining consumer adoption, a topic that got even more academic attention since the Covid-19 pandemic (Carbó-Valverde et al., 2023; Jonker et al., 2022; Kotkowski & Polasik, 2021). To a lesser extent, some authors studied if and how digitalisation of payments has caused an impact on banking performance and stability (Chen et al., 2019; Hasan et al., 2012; Kasri et al., 2022; Meifang et al., 2018; Wu et al., 2023), as well as on the real economy (Wong et al., 2020; Zhang et al., 2019). Finally, another widely addressed theme is how financial inclusion interacts with those factors (Avom et al., 2023; Demirguç-Kunt et al., 2022; Niankara & Traoret, 2023).

In terms of payment choice, several studies showed that the mobility restrictions raised during the pandemic significantly influenced consumers' preference for cashless payment methods (Carbó-Valverde et al., 2023; Jonker et al., 2022; Kotkowski & Polasik, 2021). Research on digital payment adoption and financial inclusion has revealed a bidirectional relationship. Higher levels of financial inclusion lead to a greater likelihood of adopting digital payments (Niankara & Traoret, 2023), while increased adoption of mobile money enhances financial inclusion (Avom et al., 2023). However, while consumer adoption and financial inclusion are topics widely researched in connection with digital payments, empirical studies about its impacts on banks' performance and stability are far more limited (Panetta et al., 2023). Although the existing literature mainly suggests a positive association between these factors, the specific channels through which digital payment intensity affect bank performance are varied. Additionally, the ownership and development of the digital payment innovation, whether by the bank itself or by a third party, lead to different conclusions.

Studies on bank-owned payment innovations indicate that higher volumes of cashless and digital payment methods positively impact banks' profitability and stability measures (Hasan et al., 2012; Kasri et al., 2022) and provide cost efficiency gains (Ardizzi, 2019; Saroy et al., 2023). In contrast, research on payment innovations emerging outside the traditional financial system, such as third-party payment platforms (TPPs), mostly conducted in China, concludes that higher TPP volumes negatively affect banks' performance by reducing revenue sources and increasing costs (Chen et al., 2019). Similarly, the rise of FinTechs has been shown to adversely affect incumbent banks' profitability (Ben Naceur et al., 2023).

Therefore, there is a lack of empirical research as well as an academic consensus on the impacts of payment innovations on the performance and stability of banks. The existing research in this field tackles digitalisation of payments in a broad and conservative level, embracing all forms of cashless payment methods (ATMs, POS, credit and debit cards, e-money), which include a very large set of private and public payment system providers (PSPs). Moreover, the introduction of state-owned IPSs is a very recent development whose impacts are largely unexplored.

By studying the BCB's Pix, this paper aims to fill this gap by addressing digital payments in a unique and specific perspective, i.e. through the volumes and number of transactions of a central bank-owned IPS. While most studies focused on developed economies or China, I expand the literature by tackling the case of Brazil, which not only is an important representative of emerging economies as the largest economy in Latin America, but also has a highly developed banking system. Given it is a novelty in the field, and to the best of my knowledge, the impact of CB-owned IPSs on bank performance and stability has not been investigated and its investigation will complement the existing empirical literature on the topic. Moreover, as Pix has features of both TPP and bank-owned payment innovations, by investigating the mechanisms through which Pix affects bank performance, we are better able to understand how such innovation will help shape the financial sector. Finally, with the issuance of central bank digital currency (CBDC) leading today's economic and financial discussions, the investigation of central bank managed payment systems provides interesting guidance to its development.

Performing a fixed effects estimation on a panel dataset of 73 FIs during the period of 2020 to 2023, I found that Pix has negatively impacted the performance and stability of Brazilian banks. My results show that higher volumes and number of transactions conducted with Pix leads to lower fee incomes and net interest margins, ultimately affecting their profitability ratios. In addition, by examining differences in how traditional and digital banks responded to Pix, my findings reveal that the performance of the second group is considerably more sensitive to the BCB's IPS. In terms of stability, my results show that the individual insolvency risk of both traditional and digital banks is deteriorated by Pix, although the effect for digital banks is considerably more adverse. As FinTechs take the bigger losses, the findings emphasize important differences in the business models of both groups, especially in terms of product strategy and revenue diversification. The evidence suggests that Pix acts as a new player in the payment market, likely increasing the competition amongst Brazilian banks.

My results present interesting implications for policymakers and financial institutions. For central banks, the development and implementation of IPSs could be an effective way to foster competition in the banking sector, although it might pose a risk to the stability of digital banks and FinTechs that are highly reliant on payment services. In addition, the findings suggest that the presence of free-to-use IPSs that are fully integrated with the main banks in the country might eliminate competitive advantages originally held by digital banks. Therefore, such institutions should invest in the development and expansion of new products and services that provide greater revenue diversification.

After the Introduction, this thesis will be structured as follows: the Literature Review and Theoretical Framework segment will look into the theories, empirical research and main findings on this topic, which will serve as the foundation for the development of my hypotheses; next I present the Data & Methodology which will be used in this paper, including the description of the sample and data sources, a motivation for the variables used and the empirical strategy; the Empirical Findings part will present and discuss the results achieved; and finally the Discussion and Conclusion will provide a summary of the paper, discuss important limitations and implications for future research.

2. Literature Review and Theoretical Framework

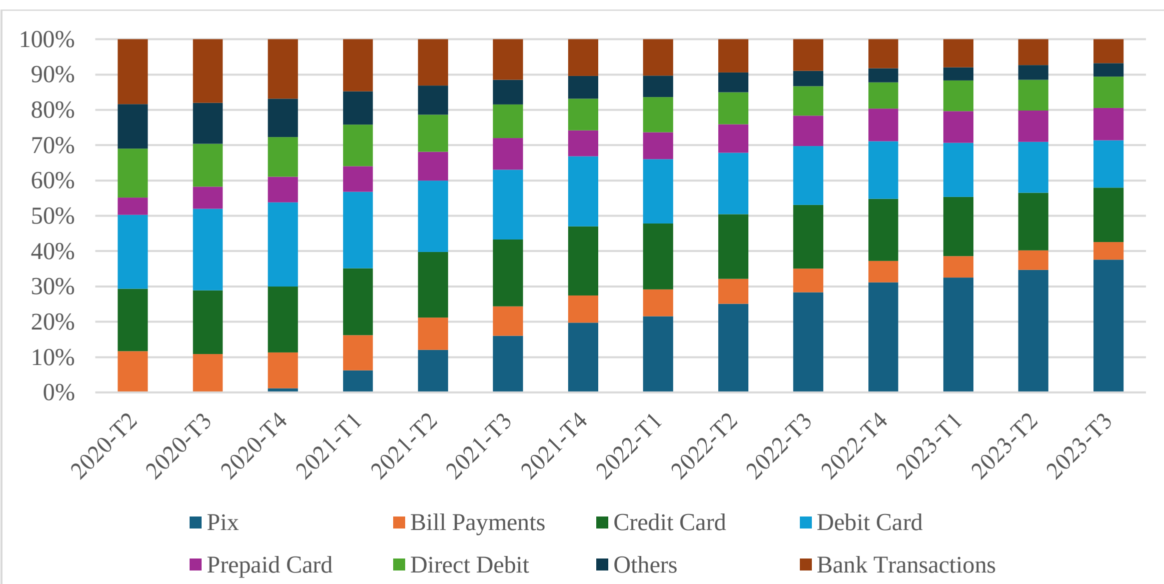
2.1 Pix, Digital Payment Adoption and Financial Inclusion

In 2013, a ruling granted the Central Bank of Brazil the legal mandate to ensure the solidity, efficiency, and proper functioning of the country's payment system. The objectives were to promote competition, financial inclusion, and transparency within payment services, as well as to position the CB a key actor in the development of payment innovations (BCB, 2022). Under such mandate, the BCB developed Pix, an instant payment scheme available to people, companies and government entities, in which the central bank is the sole system operator and rulebook owner. The payment system was officially launched in November 2020, during the Covid-19 pandemic, and has since then spiked in popularity. Amongst the many features of Pix, the Bank of International

Settlements (BIS) highlighted two main factors to explain its success: (i) the mandatory participation of large FIs, i.e. institutions with over 500,000 transaction accounts, and (ii) the centralized governance structure in the BCB (Duarte et al., 2022).

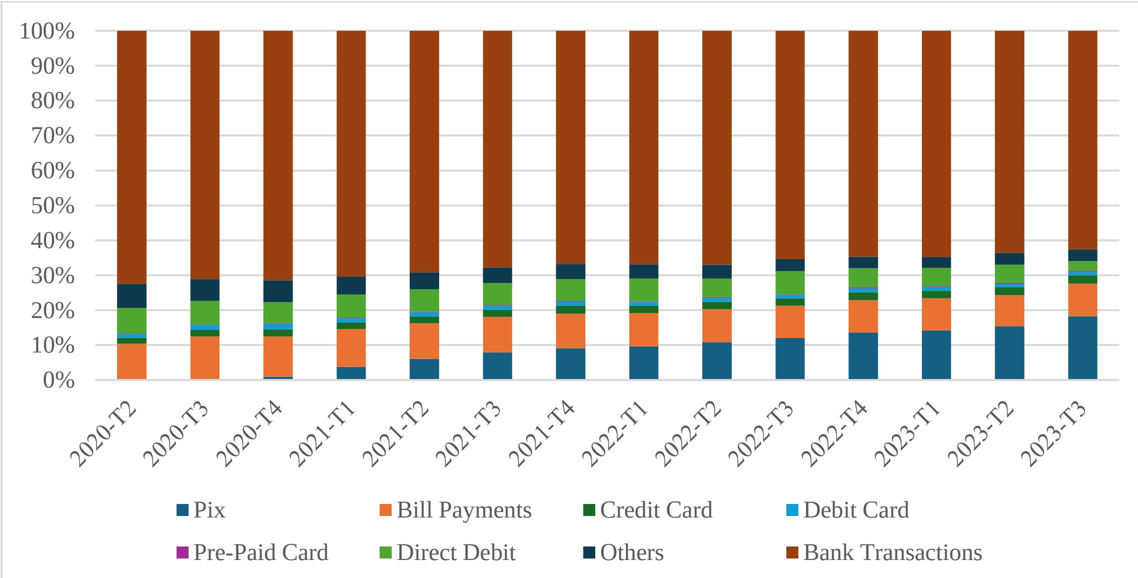
Figure 1 illustrates the popularity of that payment method in contrast to other alternatives provided by the country's financial system. In 3Q2023, Pix registered a total of 11.19 billion transactions, becoming by far the most popular payment method, accounting for 39% of the total amount of non-cash transactions in the country. Figure 2 shows the total financial volume of Pix transactions compared to other forms of cashless payment methods throughout the period. Pix was responsible for over 18% of the transactions volume in 3Q2023, surpassing card and bill payments. However, bank transactions (inter and intra-bank transfers) still dominate the country with around 63% of the market share. According to the BCB (2023), this is explained by two main reasons: (i) Pix is mostly used for low value transactions, with 61% of Pix transactions below R$100 as of December 2022; and (ii) Pix is primarily used in P2P and P2B transactions and has daily volume limits for safety purposes. Therefore, very large B2B transactions still rely mainly on bank transfers.

Figure 1: Market Share of Cashless Payment Methods (transactions)



Source: Author's own preparation based on 'Pix Statistics' webpage of BCB (2024)

Figure 2: Market Share of Cashless Payment Methods (volumes)



Source: Author's own preparation based on 'Pix Statistics' webpage of BCB (2024)

There has been an extensive literature and empirical research on the uptake of payment innovations which can help us understand the remarkable adoption of Pix in Brazil. Research has shown that the Covid-19 pandemic played a key role in the intensification of cashless payment trend among consumers. Based on a unique daily diary of payments in the Netherlands between January 2018 and December 2021, Jonker et al. (2022) studied the effect of two lockdown periods on the Dutch consumers' preference for payment methods at the POS and found that the pandemic increased the likelihood of using card payments by 12 percent after the first lock down period. Carbó-Valverde et al. (2023) studied if the mobility restrictions during the pandemic impacted the consumers payment choices at physical establishments in Spain. They found out that stricter mobility restrictions were associated with higher usage of cashless instruments. Both studies concluded that the effect persisted after the lock-down periods.

In 2022, the World Bank published The Global Findex Database 2021, which also highlights important developments on the digitalisation of financial services. The database was constructed by Demirguç-Kunt et al. (2022) based on a survey conducted with 128,000 adults over 123 economies during the Covid-19 pandemic. Specifically with regards to digital payments, by 2021 almost 95% of adults in advanced economies received or sent payments digitally, while in developing economies, that share increased from 35% in 2014 to 57% in 2021. The authors also provide insights on the important nexus between financial inclusion – measured through account ownership, utilisation of digital payments and adoption of further financial services – and digital payments. For instance, they claim that by receiving payments directly into a bank account, it is more likely that customers will leave them as savings, and therefore potentially have their credit limits increased if the payments are considered as income documentation by the bank. That is specially the case of government transfers, an income tool widely adopted during the Covid-19 recession.

Further research has explored the association between financial inclusion and digital payment adoption, revealing a bidirectional relationship where each enhances the other. Using data from the Global Findex database, Niankara and Traoret (2023) analysed whether financial inclusion impacts the uptake of digital payments. They found that individuals who are more financially included are more likely to use digital payment methods. Alternatively, Avom et al. (2023) analysed a sample of 50 African countries and found that mobile money adoption increased financial inclusion in Africa by 16 to 18%. As previously mentioned, one of the key goals of the BCB's instant payment system is to promote financial inclusion – it claims that Pix was responsible to financially include 71.5 million Brazilians by 2022. Although the empirical impact of Pix on financial inclusion is not the focus of this research, this paper assumes that Pix has positively affected financial inclusion within the country.

2.2 Impact of Payments Innovation on Bank's Performance and Stability

Since the financial crisis of 2008, the financial industry has seen a noteworthy growth in information and communication technologies that is leading to an increasingly more digitalised and data-driven sector. The literature, however, is not conclusive when it comes to digital innovations' impact on the traditional banking system. Ekinci (2021) classifies digitalisation as a technology supply shock that impacts productivity, efficiency, competition and employment on the financial sector. The adoption of technology can generate important productivity and efficiency gains to banks (Ekinci, 2021), though they are only materialised when implemented across the whole industry, rather than by firms individually (Saroy et al., 2023). On the other hand, Arnold and Jeffrey (2016) discuss the disruptive potential of digital innovations in the financial sector. Developments in technology can dramatically lower production costs, resulting in "improved value through lower pricing" as new firms focus on a specific service or product. Concerning the payments market specifically, the authors argue that the entry of new players that offer digital, safe and cheaper solutions like Paypal, Facebook, Apple and Google can potentially reduce traditional banks' profits with the service. This segment will be sub-divided into a review of the literature on bank performance and financial stability when addressed in relation to payment innovations.

2.2.1 Bank Performance

To better understand the impact of payment digitalisation on bank performance, it is crucial to review the channels through which payment services affect a bank's operations. Bank revenue is typically comprised of interest and non-interest income. While interest income refers to general lending business, the non-interest income derives from commissions and fees of other banking products and services, such as account management, brokerage, cards and payments. As the main issuers of cards, banks are traditionally the central players in the payment ecosystem, and they generate income from commissions over purchases with cards and interchange fees paid by merchants (Arnold & Jeffrey, 2016). Although payment services directly impact the non-interest income of banks, it can also contribute to interest-income generation by attracting deposits (Hasan et al., 2012) and offering cross-selling strategies for loans and other types of interest-bearing products (Ardizzi et al., 2019; Demirguç-Kunt et al., 2022). On the costs side, CBs around the world have repeatedly reinforced the cost advantages of digital payments over traditional paper-based payments (Aridizi et al., 2019), which ultimately is passed to final consumers. For banks, the adoption of digital payment technologies can reduce expenditure on fixed assets and labour costs (Saroy et al., 2023), therefore generating cost efficiency gains.

While there is a prominent lack of research focusing on purely digital or instant payment methods like Pix, many academics have empirically studied how cashless instruments and payment innovations have impacted the performance and stability of banks. Although the existing literature mainly suggests a positive association between these factors, the specific channels through which digital payment intensity affect bank performance are varied. Moreover, whether the digital payment innovation is owned and developed by the bank or by a third-party led to distinct conclusions.

A prominent study in the field was led by Hasan et al. (2012) who examined the relationship between retail payment market infrastructure and bank overall performance and stability, by studying a large panel dataset of 3,370 banks across all 27 EU countries between 2000-2007.

Among the independent variables used, they focus on the intensity of payments, measured by the total amount of cashless transactions to population, and the level of payment technology, proxied by the total number of POS terminals to population. For the measurement of bank performance, the authors used the banks' profitability indicators of return on assets (ROA) and return on equity (ROE) as dependent variables. They found that both the intensity of cashless transactions and the level of payment technology are associated with better performance. To understand the mechanisms through which performance was affected, they used net interest and net fee income as dependent variables. Although the effect of the independent variables on both income indicators were significant and positive, the impact of cashless transactions on net fee income was two times larger.

There is further evidence that digital payments have a positive impact on banking business as many studies focused on the cost efficiency gains of such innovations. Ardizzi et al. (2019) analysed a panel of 651 financial institutions over 2006-2010 in Italy to find out the association of IT innovation and bank cost efficiency. They proxied payment innovation by the share of ATMs owned by the bank over its ATMs and physical OTC branches, and by the share of electronic transactions over total transactions. The authors found that while ATM diffusion has no impact on cost efficiency, a larger share of electronic payments generate efficiency gains to banks. This effect was also verified in emerging economies. Saroy et al. (2023) studied the impact of digital payment adoption, measured by an index that considers the volume of NEFT and card transactions as well as the number of ATMs and POS deployed by the bank, on technical and cost efficiency in a panel of 41 Indian banks across 8 years. The authors found that digital payments adoption positively affects banks' performance by reducing their operational costs, rather than increasing their income.

While the outlined literature focuses on digital payment infrastructures that are developed and owned by the banks themselves (ATMs, POS and cards), another strand of literature investigated if third-party payment platforms, posts similar effects on banks' performance. The traditional view is that TPPs challenge the financial industry by providing customers with lower charges and more flexibility, thereby attracting deposits from the banking system (Meifang et al., 2018). This increased competition for deposits would make banks have to increase their interest on deposits to gain attractivity (Chen et al., 2019). Through an analysis of a panel of 200 Chinese banks between 2011-2016, Chen et al. (2019) found that TPP volumes negatively impacted the banks' performance, mainly through reducing deposits and increasing interest expenses. Similarly, Ben Naceur et al. (2023) found that higher transaction volumes of FinTechs negatively impacts incumbent financial institution's performance through lower interest income and higher operational costs. The authors argue that the emergence of FinTechs firms apply competitive pressure towards traditional banks, affecting their profitability. In line with Arnold and Jeffrey (2016), both findings support the idea of disruptive digital financial innovations and its harmful effects on traditional banks' profits.

2.2.2 Financial Stability

Bank financial stability has been broadly addressed in the literature as it provides policymakers with important regulatory insights and offers executives with valuable risk management perspectives. However, the interaction of payment innovation and bank stability has been largely overlooked by academics, with a few notable exceptions. In addition, given that promoting financial inclusion and fostering competition feature among the BCB's primary goals with the development of Pix, it is crucial to review how these factors affect banking stability.

Among the exceptions mentioned, there are two studies that stand out for examining stability directly in relation with digital payments. Firstly, the study conducted by Hasan et al. (2012), discussed in the previous sub-section, also assessed the impact of payment innovation on bank stability, proxied by their Z-Scores. The authors saw that higher number of cashless transactions per capita and higher adoption of payment technology contributes to lower levels of insolvency risk in the banking industry, likely related to greater revenue stability, as their performance indicators are positively affected. Their findings are supported by a more recent study conducted by Kasri et al. (2022). The authors investigated the impact of digital payment methods, proxied by the total volume of card and electronic payments to GDP on both bank and country-level Z-Score of the banking industry in Indonesia between January 2013 and July 2021. They concluded that higher volumes of digital payments are associated with improved financial stability both in the short and in the long-run, due to an increase of fee-based income arising from digital transactions, further indicating that better revenue stability leads to lower insolvency risk.

In contrast, when considering the indirect mechanisms through which Pix could affect bank stability, namely financial inclusion and competition, the literature is far more abundant. Generally, it suggests that higher levels of financial inclusiveness leads to greater banking stability, with the main argument behind it being that financial inclusion provides banks with diversification benefits both in their assets and liabilities (Danisman & Tarazi, 2020). A diversified retail deposit funding is cheaper and less volatile than wholesale funding which reduces the banks' insolvency risk (Ahamed & Mallick, 2019). The positive impact of financial inclusion on bank stability was empirically demonstrated by a number of authors. Ahamed and Mallick (2019) analysed a worldwide sample of banks and showed that higher levels of financial inclusion led to greater individual bank stability. Danisman and Tarazi (2020) studied a panel of banks of all EU and found that higher number of bank account ownerships and higher share of digital payment adoption among adults has led to lower bank default risk, measured by the Z-Score. When institutions on emerging countries, Wang and Luo (2022) verified that financial inclusion positively affects bank stability, mainly through increased operational efficiency, better risk management due to asset portfolio diversification, and stabler funding sources.

On the other hand, if increased adoption of digital innovations can lead to higher competition among financial institutions, as seen in the cases of TPPs and FinTechs, Pix might post an adverse effect on financial stability. Leroy and Lucotte (2017) found evidence supporting a trade-off between competition and stability in European banks. The authors showed that higher measures of competition and lower market power held by banks, proxied by the Lerner index, are associated with greater individual risk-taking and lower Z-Scores. Saif-Alyousfi et al. (2020) found similar results for emerging economies with the additional conclusion that lower concentration also decreases financial stability.

Therefore, all these factors need to be considered when hypothesizing the effects of Pix on the financial stability of Brazilian banks. Nonetheless, it is important to note that the impact of Pix on financial inclusion and competition measures are outside of the scope of this research.

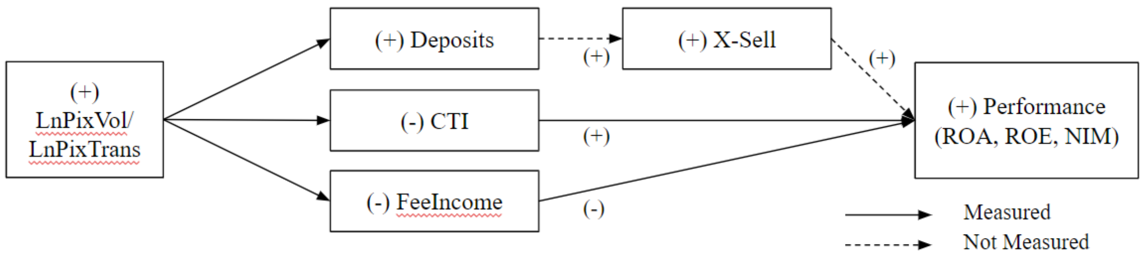
2.3 Research Questions and Hypotheses Development

In summary, the existing literature on the field of payment innovations is quite extensive and varied. The bulk of the research in this topic has tackled the angle of consumer adoption, although impacts on bank performance and stability have been addressed to a lesser extent. However, such studies have mainly used a broad definition of digital payments, encompassing a variety of cashless instruments, such as credit and debit cards, ATMs, POS terminals and electronic transfers, most of which developed and owned by the banks themselves. When reviewing purely digital payment methods that emerged outside of the banking system, such as TPPs, most of research was conducted in China and reached divergent conclusions. Moreover, studies covering the recent advent of IPSs, especially CB-owned schemes such as Pix, are considerably scarce and a novelty in the field. As mentioned, the BCB's IPS was introduced with the purpose of promoting financial inclusion, foster competition in the payment market, improve the safety and reliability of payment systems and lower its costs for population. In order to achieve this, Pix has several unique characteristics that distinguish it from existing payment innovations, including: (i) mandatory participation of financial institutions with over 500,000 clients, ensuring all major banks in the country offer this payment method to its clients; (ii) 24/7 availability, in contrast with existing bank transfer methods; (iii) free-to-use for people and very low cost for businesses of R$ 0.01 per transaction; and (iv) safety backed by the BCB's credibility. Therefore, this thesis aims at answering the following questions: (a) does Pix impact the Brazilian banks performance? And (b) does Pix impact the stability of Brazilian banking industry? Based on the theories and empirical evidence presented in this section, I developed the following two hypotheses.

The first one relates to Pix and Brazilian banks' performance. Pix can only be used through a bank account, therefore is fully integrated with the major players in the banking system. Due to its attractive features and intense adoption among Brazilians, I argue that Pix is similar to a bank-owned innovation that has expanded the client base of Brazilian banks and generated a positive impact on its deposits. With more deposits, banks are better funded and can increase their borrowings, generating higher interest income (Hasan et al., 2012). This effect is intensified given cross-selling opportunities that stem from new clients (Ardizzi et al., 2019; Demirguç-Kunt et al., 2022). However, fee income will likely be negatively impacted by Pix. As Pix is free for people and has lower costs for merchants, clients will migrate from traditional bank-owned payment instruments, impacting their fee income, as suggested by Arnold and Jeffrey (2016). Nonetheless, such migration will likely result in lower operating costs for banks as they won't need to spend as many resources on labour and infrastructure associated with payment processing and settlement, generating cost efficiency gains (Ardizzi et al., 2019; Ekinci, 2021; Saroy et al., 2023). As a result, I hypothesize that the banks' overall profitability will be positively impacted by Pix, in line with the findings of Hasan et al. (2012):

- H1: Pix's financial volume and number of transactions will positively impact the performance of Brazilian banks

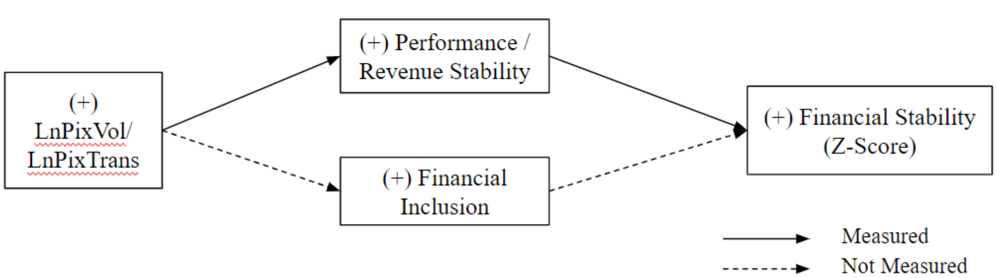
Figure 3: Hypothesis Framework – Pix and Bank Performance



The second hypothesis refers to Pix and the stability of Brazilian banks. The remarkable adoption of Pix among Brazilians suggests that it has been successful in promoting financial inclusion, as claimed by the BCB. Greater financial inclusion, in turn, has proven to increase banking stability (Ahamed & Mallick, 2019; Danisman & Tarazi, 2020; Wang & Luo, 2022). Although higher competition in the banking system is typically associated with lower levels of stability – due to banks facing stronger competitive pressure having less stable sources of revenue and higher costs (Leroy & Lucotte, 2017; Saif-Alyousfi et al., 2020) – I argue that Pix has a synergetic relationship with banks. Such relationship improves performance and lowers costs, in line with H1. Therefore, I hypothesize that Pix will increase the stability of Brazilian banks, in accordance with the findings of Hasan et al. (2012), Danisman and Tarazi (2020) and Kasri et al. (2022).

- H2: Pix's financial volume and number of transactions will positively impact financial stability of Brazilian banks

Figure 4: Hypothesis framework: Pix and Financial Stability



3. Data & Methodology

3.1 Sample and Data Sources

As this paper aims at unveiling the impact of Pix in the Brazilian banking system, it is reasonable only to include institutions that are active participants of the instant payment scheme. Therefore, the original sample consisted of all 815 financial institutions that are active Pix operators. However, as the scope of this research lies on the banking system, I excluded all non-bank institutions from the sample, except for a few payment institutions that had over 500.000 active clients and offered deposit accounts. According to the current regulation, such FIs are mandatory participants in the Pix scheme. It is important to note that a few digital banks are registered within the BCB as financial and payment institutions to avoid stricter regulatory framework, making up what is usually referred as the "shadow banking system". It is the case of institutions like Nubank, Neon, Mercado Pago and PagSeguro, who all offer digital deposit accounts, credit and debit cards and personal loans. The result is a final sample of 73 financial institutions, consisting of 46 traditional banks and 27 digital banks. The data has a quarterly frequency, starting in the 4Q2020, quarter in which Pix was officially launched, until the 3Q2023, which is the latest available in the BCB dataset, therefore covering a total of 12 quarters.

All data for the banks' balance sheet items was downloaded through the online BCB dataset "IF.data" to ensure consistency throughout the whole analysed period. This database is periodically updated and consolidates balance-sheet and income statement information on all the financial institutions overseen by the CB on a quarterly basis. The publication of mid-year and end-year values consolidates the data over the two previous quarters, following the country's authorities' accounting rules. Therefore, additional calculation had to be done to isolate the variables for the 2nd and 4th quarters. The total volume and quantity of transactions of Pix payments were also retrieved from the BCB "Pix statistics" webpage. Macroeconomic indicators were collected from the Brazilian National Institute of Geography and Statistics (IBGE).

3.2 Variables

3.2.1 Pix Variables (Main Independent)

Most of research addressing digital payments relies on two possible measures: transacted volumes (measured in the country's currency), and number of transactions made. Therefore, this paper will employ both approaches to measure the intensity of Pix. The first one *(LnPixVol)* considers the natural logarithm of financial volume (in R$) of all Pix transactions during the quarter. Total volumes, whether scaled by GDP or in its absolute values, were used to measure digital payments by several authors (Chen et al., 2019; Kasri et al., 2022; Meifang et al., 2018; Zhang et al., 2019). The second one *(LnPixTrans)* considers the natural logarithm of the total number of Pix transactions in the quarter. Number of transactions scaled by population was used by Hasan et al. (2012) to measure digital payment intensity within a country. Since the scaling by either population or GDP were typically used in papers that compared country heterogeneity, I will use only the natural logarithm of the absolute values. By including both metrics, it will be possible to evaluate whether is financial volume or number of transactions that causes the stronger impact.

3.2.2 Performance and Transmission Mechanism Variables (Dependent)

Bank performance has been subject of numerous empirical studies throughout the decades and although there is not a consensus on a unique interpretation and measurement indicator (Koroleva and Kudryavtseva, 2019), it has been conventionally proxied by profits, revenues and economic efficiency. Profitability of banks has been traditionally proxied by return on assets (ROA) and return on equity (ROE) as they show the banks' management ability to generate profits in terms of their total assets and equity. Those ratios are the most used measures of bank performance and were applied by several papers through decades of research (Athanasoglou et al., 2008; Ben Naceur & Goaied, 2008; Chen et al., 2019; Hasan et al., 2012). Another strand of literature used net interest margin (NIM) as a measure of bank performance, although it is sometimes referred as a transmission mechanism. This accounting ratio measures the spread between the interest paid by the bank for its funding and the interest charged on its loans, and it can be seen as a measure of bank "efficiency" (Demirguç-Kunt & Huizinga, 1999). As lending operations are banks main business, the NIM approach was used by academics such as Demirguç-Kunt and Huizinga (1999), and Saona (2016). Therefore, *ROA*, *ROE* and *NIM* will all be used as dependent variables in the econometric regression for robustness of the results. I also include the additional disaggregated performance variables: fee income-to-total income *(FeeIncome),* cost-to-income ratio *(CTI)* and deposits-to-assets ratio *(Deposits)* as measures of performance transmission mechanism. Although these additional variables are also included as intra-bank control variables in the regression model, I hypothesized that they will be directly impacted by Pix.

3.2.3 Stability Variables (Dependent)

In line with the empirical research covered in the Literature Review, I will proxy financial stability by the Z-Score of each bank. The Z-Score is computed as $\frac{ROA+\frac{Equity}{Assets}}{\sigma ROA}$, where σROA is the standard deviation of ROA, which is estimated over the sample period, following Hasan et al. (2012). The Z-Score is a proxy for insolvency risk of banks and indicates the amount of standard deviations that the banks' average ROA must fall so that its equity to be completely wiped out, thus higher values of Z-Score are associated with lower default probabilities (Saif-Alyousfi et al, 2020). Therefore, the variable *(StabilityROA)* will measure the bank-level Z-Score. For robustness, an additional measure of bank risk is captured by the variable *(LLP)* that measures the banks total loan loss provision divided by its total loans. Given the banks' primary business of financial intermediation, credit risk can be considered its main source of risk. The use of LLP as risk measure follows the empirical research of Saif-Alyousfi et al (2020).

3.2.4 Control Variables (Independent)

Bank performance is typically expressed as a function of internal and external determinants (Athanasoglou et al., 2008). Internal determinants relate to variables that the bank's management can directly control, while the external ones are factors associated with the macroeconomic, market and regulatory environment in which the bank operates (Athanasoglou et al., 2008; Saona 2016). Saona (2016) studied the intra and extra-bank determinants of bank profitability in Latin America and showed that internal factors should consider: capital ratio, revenue diversification, size, credit risk, concentration, loans and deposits. External factors include: financial development, regulatory system, inflation rate, growth of GDP per capita, reserve requirements and financial stability. Demirguç-Kunt and Huizinga (1999), Afanasieff et al. (2002), and Ben Naceur and Goaied (2008) also included a cost factor as internal determinants. However, as reserve requirements and regulatory system variables are mostly used to study heterogeneity across different countries, they will be excluded from my model, which only considers banks operating in Brazil. Moreover, financial development indicator was also removed from the model due to high correlation with other variables.

Therefore, following Hasan et al. (2012), Saona (2016) and Chen et al. (2019), the control variables included in my model are as follows. Among bank controls: *(Equity)* measures capital ratio as the equity ratio; revenue diversification *(FeeIncome)* as the fee income over total income; bank size *(Size)* will be proxied by the log of total assets; bank loans *(Loans)* are measured by the loan-to-asset ratio; credit risk *(LLP)* is measured by the loan loss provision over total loans; bank concentration *(CR3)* is measured by the asset market share of the three largest banks in the country; bank deposits *(Deposits)* are measured by total deposits over total assets; and cost-to-income ratio *(CTI)* calculated as operating expenses divided by the sum of net interest income and other income. The external controls included are: inflation rate *(Infl)*; the growth of GDP *(GDPg)*; and financial stability *(StabilityROA),* measured by the Z-Score of ROA.

In addition, to verify heterogeneity among banks, I classified the data between Traditional and Digital Banks. While the classification of ownership type is objective and provided by the regulator's dataset, the BCB does not provide an actual category of digital banks. It claims that it is a self-denominated category based on marketing and operational strategies, marked by an exclusively remote client relationship, i.e. inexistence of physical branches (BCB, 2020). The BIS has a similar understanding: digital banks are banking institutions whose business model depends on intense usage of technology and data, high reliance on internet and mobile apps and reduced number of branches and human interaction (BIS, 2023). Building upon the definitions of the BCB and the BIS, this paper will consider digital banks as the banking institutions that actively market themselves as "digital banks" in their official webpages. The following table summarizes all the variables information.

Table 1: Variables List

Variable Type	Variable Name	Definition / Calculation	Source
Main Independent	*LnPixVol*	Natural Logarithm of Total Financial Volume of Pix Transactions	BCB "Pix Statistics" web page; author's calculation
	LnPixTrans	Natural Logarithm of Total Number of Pix Transactions	
Performance Measure	*ROA*	Net Income / Total Assets (%)	BCB "IF.Data" database; author's calculations
	ROE	Net Income / Total Equity (%)	
	NIM	Net Interest Income / Total Assets (%)	
Transmission Mechanisms	*Deposits*	Total Deposits / Total Assets (%)	
	FeeIncome	Fee Income / Total Income (%)	
	CTI	Operating Expenses / (Operating Income + Net Interest Income) (%)	
Stability Measure	*StabilityROA*	Z-Score = (ROA + Equity Ratio) / Standard Deviation of ROA	

	LLP	Loan Loss Provisions / Total Loans (%)	
Controls	*Size*	Natural Logarithm of Total Assets	
	Equity	Total Equity / Total Assets (%)	
	Loans	Total Loans / Total Assets (%)	
	CR3	Asset Market Share of 3 Largest Banks (%)	
	GDPg	Quarterly Growth of GDP per capita (%)	IBGE
	Infl	Quarterly Inflation Rate (%)	

3.3 Descriptive Statistics

The table below provides a summary of the main statistics of the variables.

Table 2: Summary Statistics

	N	Mean	Std. Dev.	min	p1	p25	Median	p75	p99	max
LnPixVol	835	21.306	0.908	18.825	18.825	21.166	21.45	21.961	22.226	22.226
LnPixTrans	835	15.075	1.127	12.079	12.079	14.867	15.262	15.912	16.231	16.231
ROA	835	-0.026	1.482	-16.370	-7.247	0.036	0.253	0.467	1.754	4.029
ROE	835	-0.616	18.955	-299.475	-92.848	0.355	2.739	4.704	16.903	39.742
NIM	835	1.224	1.434	-7.966	-1.651	0.433	0.946	1.723	6.192	9.841
Deposits	835	48.477	21.575	0.541	2.665	33.67	47.375	66.135	87.688	94.732
FeeIncome	835	16.095	19.535	0.028	0.041	3.889	8.332	19.296	85.572	94.424
CTI	835	100.957	88.297	2.396	25.521	65.095	84.006	100.85	595.287	994.549
StabilityROA	835	63.592	60.553	-2.050	0.256	17.647	43.583	98.408	274.031	375.704
LLP	835	4.522	5.744	0.000	0.000	1.027	2.807	5.726	31.404	41.909
Equity	835	11.696	8.972	0.872	1.575	7.037	9.478	13.514	51.619	85.120
Size	835	16.325	2.262	9.918	10.877	14.617	16.26	17.778	21.343	21.482
Loans	835	39.731	26.330	0.000	0.000	18.405	39.154	60.733	94.761	98.938
Infl	835	1.834	1.261	-1.320	-1.320	0.760	2.050	2.960	3.200	3.200
GDPg	835	0.819	0.933	-0.200	-0.200	-0.100	0.500	1.200	3.200	3.200
CR3	835	49.211	0.369	48.680	48.680	48.840	49.180	49.540	49.860	49.860

Looking at the descriptive statistics we observe the presence of very large outliers in many of the variables, which is mainly attributed to the presence of the digital banks in the dataset. Such institutions have distinct business models and growth strategies, reflected in their financial indicators. To compete with traditional banks, FinTechs usually incur high operating costs and net losses during their initial years to gain market share. As an illustration, Nubank, Brazil’s largest digital bank founded in 2013, only registered its first positive net result in 2022. Figures 5 and 6 show this difference in the dataset: While 43% of digital banks’ observations registered negative ROA, that value was only of 10% for the traditional banks. In terms of the Cost-to-Income ratio, 47% of the observations for digital banks had CTIs over 100%, while only 14% for traditional banks.

Figure 5: ROA and Cost-to-Income ratio histograms of Traditional Banks

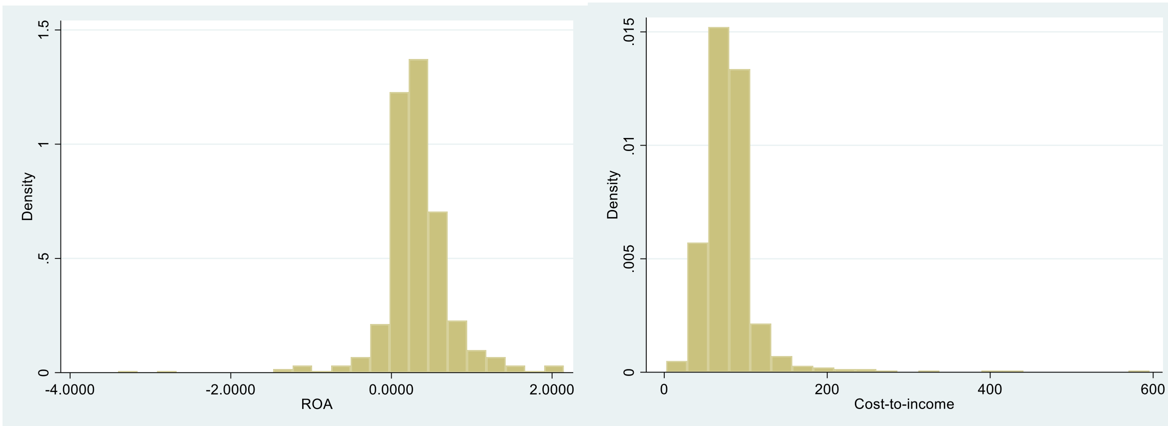
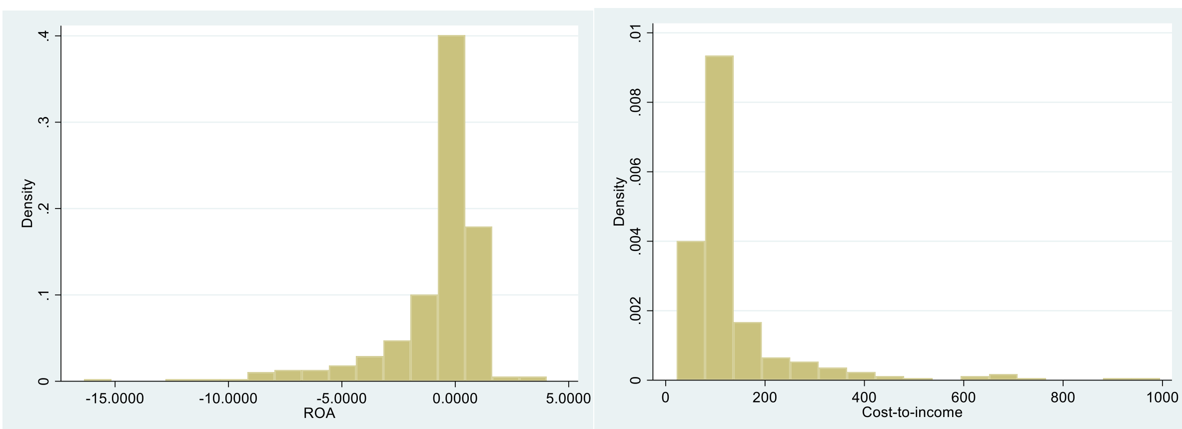


Figure 6: ROA and Cost-to-Income ratio histograms of Digital Banks



In addition, as mentioned before, a great share of digital banks is registered within the BCB as payment institutions rather than banks. That often means the requirement to split their consumer credit and financing operations into another entity, remaining mostly with their payment and deposit services, which explains the zero values for LLP and very high Fee Income figures. Finally, as some of the digital banks in the sample are owned or were recently acquired by large institutions and private investors, they registered especially high levels of capitalization. That is the case of Banco Capital S.A., acquired and highly capitalized in the 3Q2020 by Social Bank, which is responsible for 10 of the 15 largest Equity ratio observations in the dataset.

Therefore, to address the presence of outliers in the dataset and considering that digital banks comprise of 36% of the FIs, the sample was split into three groups, and the variables winsorized at the 99% level (indicated by adding "99" to their names). This paper will thus investigate the impacts of Pix across three datasets: a complete dataset that includes all 73 FIs; a dataset with only traditional banks (46); and a dataset with only digital banks (27). Tables 3 and 4 present the resulting summary statistics for the traditional and digital banks datasets.

Table 3: Summary Statistics – Traditional Banks

	N	Mean	Std. Dev.	min	p25	Median	p75	max
LnPixVol	543	21.301	0.915	18.825	21.166	21.450	21.961	22.226
LnPixTrans	543	15.069	1.136	12.079	14.867	15.262	15.912	16.231
ROA 99	543	0.323	0.384	-1.116	0.131	0.298	0.488	1.598
ROE 99	543	3.134	3.910	-15.636	1.559	3.273	5.119	13.894
NIM 99	543	1.260	1.353	-1.670	0.458	0.915	1.635	6.243
Deposits 99	543	47.65	22.504	4.339	30.011	42.688	68.541	90.705
FeeIncome 99	543	10.599	12.217	0.041	3.070	6.489	13.716	74.328
CTI 99	543	79.672	33.067	24.973	59.809	76.627	90.696	243.545
StabilityROA99	543	73.388	52.549	4.277	32.581	60.466	105.186	270.505
LLP 99	543	4.115	4.356	0.000	1.087	3.155	5.437	27.809
Equity 99	543	10.179	4.862	2.366	7.229	9.095	12.588	26.978
Size 99	543	16.758	2.364	12.415	14.520	16.628	18.509	21.394
Loans 99	543	42.385	26.020	0.000	21.194	40.531	62.949	95.681
Infl	543	1.835	1.263	-1.32	0.760	2.050	3.020	3.200
GDPg	543	0.824	0.939	-0.200	-0.100	0.500	1.200	3.200
CR3	543	49.208	0.368	48.68	48.97	49.180	49.540	49.86

Table 4: Summary Statistics – Digital Banks

	N	Mean	Std. Dev.	min	p25	Median	p75	max
LnPixVol	292	21.315	0.896	18.825	21.166	21.553	21.961	22.226
LnPixTrans	292	15.085	1.113	12.079	14.867	15.387	15.912	16.231
ROA 99	292	-0.655	2.160	-11.159	-0.939	0.051	0.419	2.333
ROE 99	292	-6.809	24.447	-140.55	-6.910	0.485	3.458	22.166
NIM 99	292	1.177	1.278	-1.651	0.335	1.000	1.809	6.192
Deposits 99	292	49.994	19.434	2.442	40.563	51.153	63.388	86.347
FeeIncome 99	292	26.235	25.413	0.040	6.717	15.995	36.697	91.364
CTI 99	292	136.387	119.328	34.312	81.785	98.014	128.781	719.401
StabilityROA99	292	44.444	65.877	-0.490	6.355	15.462	37.872	305.278
LLP 99	292	5.066	6.793	0.000	0.815	2.372	6.139	31.856
Equity 99	292	14.223	12.393	1.225	6.412	11.369	15.662	66.584
Size 99	292	15.523	1.790	10.242	14.832	15.692	16.822	18.730
Loans 99	292	34.756	26.144	0.000	8.635	33.856	58.231	80.517
Infl	292	1.832	1.260	-1.320	0.760	2.090	2.960	3.200
GDPg	292	0.808	0.925	-0.200	-0.100	0.500	1.200	3.200
CR3	292	49.215	0.372	48.680	48.840	49.180	49.540	49.860

3.4 Empirical Model

Based on the literature discussion and previous empirical studies, I formulate the following static regression model to uncover the association between Pix total volume *(LnPixVol)* and number of transactions *(LnPixTrans)* on the performance and stability of Brazilian banks:

$$
\begin{aligned}
Performance_{i,t} &\\
&= \beta_0 + \beta_1 LnPixVol_{i,t} + \beta_2 LnPixTrans_{i,t} + \gamma IntraBankControls_{i,t} \\
&+ \delta ExtraBankControls_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

$$
\begin{aligned}
Stability_{i,t} = \beta_0 + \beta_1 LnPixVol_{i,t} + \beta_2 LnPixTrans_{i,t} + \gamma IntraBankControls_{i,t} \\
+ \delta ExtraBankControls_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

The proposed model follows closely that of Hasan et al. (2012) and Chen et al. (2019), who analysed the impact of payment innovation on bank performance and risk in a very similar specification. Ben Naceur et al. (2023) used a very similar model to study the impact of fintech transactional volume on the performance of traditional banks. Wong et al. (2020) also used a comparable specification to check the impact of cashless payments on economic growth. Given no significant correlation among the independent variables, the model should not have multicollinearity issues (see complete correlation matrix in table A7 of the Appendix).

Given that the model in question is static, i.e. does not contain a lag of the dependent variable, the estimation methods considered are Bank Fixed Effects and Random Effects, as Pooled OLS is discarded due to the requirement of strong assumptions that do not fit the model. Time Fixed Effects is also discarded as Pix variables are only time varying and would be excluded from the regression.

To find the best suitable estimator, the Hausman test was conducted in the complete dataset with ROA as dependent variable. Given the low p-value of 0.000 we reject the null hypothesis that the difference in the coefficients of FE and RE is not systematic and therefore take Fixed Effects as the preferred regression method.

Table 5: Hausman Test Result

Hausman Test				
	FE	RE	Difference	S.E.
LnPixVol	-0.211	-0.081	-0.130	0.020
Equity	-0.061	-0.046	-0.015	0.008
FeeIncome	-0.032	-0.023	-0.009	0.004
Size	0.809	0.003	0.806	0.155
Loans	-0.010	0.002	-0.013	0.004
LLP	-0.064	-0.021	-0.044	0.007
Deposits	-0.017	-0.009	-0.008	0.004
CR3	0.078	0.085	-0.007	.
CTI	-0.001	-0.003	0.002	0.000
Infl	0.016	-0.002	0.018	.
GDPg	-0.074	-0.040	-0.033	.
StabilityROA	0.016	0.004	0.012	0.003
scalars:	chi^2 (12) =	**652.303**	rank =	12
	p-value	**0.000**	df =	12

The choice for Bank Fixed Effects is consistent with the idea that all the institutions in the sample, being from the same country, share similar characteristics. Additionally, considering most of the variables are financial indicators of each institution, it is reasonable to assume that the unobserved individual specific effects, such as management quality and corporate culture, are correlated with the regressors. The Bank FE method follows the studies of several authors who researched the performance and/or stability of banks, including Ben Naceur et al. (2023), Chen et al. (2019), Leroy and Lucotte (2017), Wang and Luo (2022). Finally, the estimation will apply heteroskedasticity-robust standard errors and clustering by time to control for autocorrelation to achieve an accurate estimation of standard errors and t-values, following Cameron and Miller (2015).

4. Empirical Findings

The empirical findings will be presented as follows: First, I discuss the impact of Pix on the banks' performance variables. Second, I investigate the transmission mechanisms that are likely to explain the variation of performance. Third, I present how Pix is affecting the stability of the banks. In the first subsection I will address the complete dataset, which considers all 73 institutions in the sample. In the second subsection I draw a comparison on the effects on performance, transmission mechanisms and stability between traditional and digital banks. In addition, I interpret the coefficient values given a 10% increase on the financial volume and number of transactions of Pix by multiplying the regression coefficient by the natural logarithm of 1.10. I use 10% as a reference value due to its economic significance, considering that over the last two years, Pix volumes and transactions registered an average quarterly growth of 14% and 19%, respectively.

4.1 Complete Dataset

4.1.1 Performance and Transmission Mechanisms

Tables 6 and 7 show the baseline regression results for the performance and transmission mechanism variables, respectively. All the coefficients are statistically significant at the 1% level. We note that the coefficient value for the *LnPixVol* variable is always larger than that of *LnPixTrans*, which indicates that the impact generated by the financial volume processed by Pix is more significant than by the number of transactions. As previously mentioned, most Pix transactions are of low amounts: 61% of transactions in 2022 were below R$100. Therefore, each additional transaction contributes relatively low to the share of financial volume transacted by Pix, which explains the lower coefficient values. Furthermore, as noted by Arnold and Jeffrey (2016), bank fee income stems from commission over the volume of processed payments, rather than the number of transactions.

As opposed to what was expected, the volume and number of Pix transactions negatively impacts the performance of Brazilian banks. A 10% increase in the financial volume of Pix (*LnPixVol*) reduces the ROA of banks by approximately 0.02 p.p., the ROE by 0.20 p.p., and the NIM by 0.03 p.p. Similarly, a 10% increase in the quantity of Pix transactions (*LnPixTrans*) reduces ROA by approximately 0.01p.p., ROE by 0.16 p.p. and NIM by 0.02 p.p. The effects are meaningful considering the median values of ROA, ROE and NIM of 0.25%, 2.74% and 0.95% respectively.

When looking at the transmission channels, we notice that Fee Income is negatively affected by Pix as predicted in the hypothesis. A 10% increase in the financial volume of Pix decreases the proportion of Fee Income to Total Income by approximately 0.33 p.p., while a 10% increase in the quantity of Pix transactions reduces that ratio by approximately 0.26 p.p. The effect is also meaningful considering the median value for Fee Income of 8.33%. However, as opposed to the hypothesized, the deposits and cost-to-income ratios of the banks are not affected by Pix, given the statistically insignificant coefficients.

Such findings suggest that, contrary to the hypothesis, Pix does not provide the banking system with an increased deposit base, higher interest income and lower costs. Instead, it decreases their performance by lowering interest margin and fee incomes of the participant institutions. The results indicate that Pix might approximate more to a new player entering the payments market that pushes competition further, rather than an innovation owned and deployed by existing banks that could lead to newer revenue streams and efficiency gains, as evidenced by Hasan et al. (2012) and Ardizzi et al. (2019). This idea is consistent with the findings of Chen et al. (2019) and his conclusions that the emergence of TPP platforms leads to an increased competition for deposits and higher interest expenses, negatively affecting the banks' profitability ratios. Similarly, Ben Naceur et al. (2023) also showed that the emergence of FinTechs has applied greater competitive pressures to traditional banks, as its higher transacted volumes led to increased interest expenses and operational costs for incumbent financial institutions.

However, as the complete dataset encompasses both traditional and digital banks, whose notable differences were addressed in the methodology section, further investigation is required to reach stronger conclusions on the impact of Pix. Given the increased variance of the variables by considering both types of banks together, the magnitude of the coefficients and its statistical significance might have been affected in the complete dataset estimation.

Table 6: Performance Regression Results – Complete Dataset

PERFORMANCE MEASURES – COMPLETE DATASET						
	(1)	(2)	(3)	(4)	(5)	(6)
	ROA_99	ROA_99	NIM_99	NIM_99	ROE_99	ROE_99
LnPixVol	**-0.1767*** **		**-0.2888*** **		**-2.1156*** **	
	(-3.75)		**(-7.30)**		**(-3.74)**	
LnPixTrans		**-0.1425*** **		**-0.2306*** **		**-1.7116*** **
		(-3.80)		**(-7.33)**		**(-3.84)**
Equity_99	-0.0489*	-0.0487*	0.0180	0.0181	1.0393***	1.0411***
	(-1.82)	(-1.81)	(1.26)	(1.28)	(4.04)	(4.04)
FeeIncome_99	-0.0171*	-0.0172*	-0.0329***	-0.0330***	-0.0938	-0.0954
	(-1.66)	(-1.67)	(-4.83)	(-4.83)	(-0.81)	(-0.82)
Size_99	0.6775***	0.6820***	-0.0621	-0.0578	13.1175***	13.1794***
	(6.00)	(5.99)	(-0.40)	(-0.38)	(7.69)	(7.70)
Loans_99	-0.0049	-0.0050	0.0062	0.0062	0.1063**	0.1060**

	(-1.01)	(-1.01)	(1.11)	(1.11)	(2.07)	(2.06)
LLP_99	-0.0677***	-0.0677***	-0.0674***	-0.0674***	-0.4552	-0.4548
	(-3.66)	(-3.67)	(-5.29)	(-5.29)	(-1.32)	(-1.32)
Deposits_99	-0.0071	-0.0070	-0.0106	-0.0105	-0.0568	-0.0562
	(-0.80)	(-0.79)	(-1.37)	(-1.37)	(-0.97)	(-0.96)
CR3	0.0981*	0.1031**	0.0817*	0.0900**	-0.2626	-0.2036
	(1.89)	(2.21)	(1.66)	(1.97)	(-0.47)	(-0.41)
CTI_99	-0.0007	-0.0007	0.0005	0.0005	-0.0047	-0.0047
	(-1.45)	(-1.45)	(1.19)	(1.20)	(-0.72)	(-0.73)
Infl	-0.0066	-0.0064	0.0033	0.0040	-0.3107	-0.3086*
	(-0.40)	(-0.40)	(0.16)	(0.20)	(-1.59)	(-1.66)
GDPg	-0.0466	-0.0429	-0.0797***	-0.0724***	-0.4754	-0.4334
	(-1.55)	(-1.54)	(-3.30)	(-3.37)	(-1.62)	(-1.61)
StabilityROA_99	0.0193***	0.0193***	0.0044	0.0044	0.0009	0.0009
	(5.16)	(5.17)	(1.48)	(1.47)	(0.02)	(0.02)
Constant	-11.5548***	-13.4942***	4.9896**	1.8254	-164.9021***	-188.1333***
	(-2.96)	(-3.97)	(1.99)	(0.73)	(-3.53)	(-4.50)
Observations	835	835	835	835	835	835
R^2	0.15	0.15	0.21	0.21	0.16	0.16
Adjusted R^2	0.14	0.14	0.20	0.20	0.15	0.15
AIC	1805.75	1805.33	1683.78	1683.47	6094.87	6094.42
BIC	1857.75	1857.34	1735.78	1735.47	6146.87	6146.43

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

Table 7: Transmission Mechanism Regression Results – Complete Dataset

TRANSMISSION MECHANISM MEASURES – COMPLETE DATASET						
	(1)	(2)	(3)	(4)	(5)	(6)
	Deposits_99	Deposits_99	FeeIncome_99	FeeIncome_99	CTI_99	CTI_99
LnPixVol	**0.0289**		**-3.4546*** **		**-4.6606**	
	(0.05)		**(-11.91)**		**(-1.40)**	
LnPixTrans		**0.0448**		**-2.7611*** **		**-3.6755**
		(0.10)		**(-12.66)**		**(-1.38)**
Equity_99	-0.8803***	-0.8808***	-0.4304***	-0.4278***	-0.5264	-0.5250
	(-6.44)	(-6.42)	(-4.48)	(-4.47)	(-0.34)	(-0.34)
FeeIncome_99	-0.1999***	-0.1990***			0.5720	0.5728

	(-5.84)	(-5.76)			(1.30)	(1.30)
Size_99	-2.3628	-2.3927	-4.7831***	-4.7177***	5.5974	5.6041
	(-1.19)	(-1.19)	(-4.58)	(-4.54)	(0.49)	(0.49)
Loans_99	-0.1632***	-0.1630***	-0.0512	-0.0513	-0.1073	-0.1067
	(-3.12)	(-3.11)	(-1.22)	(-1.22)	(-0.33)	(-0.33)
LLP_99	0.1994**	0.1994**	0.0132	0.0139	0.1310	0.1321
	(2.26)	(2.26)	(0.22)	(0.23)	(0.11)	(0.11)
CR3	-0.5286	-0.5280	0.7227	0.8199	-13.0162**	-12.8809**
	(-0.87)	(-0.89)	(1.00)	(1.18)	(-2.49)	(-2.47)
CTI_99	0.0060	0.0060	0.0067	0.0067		
	(1.14)	(1.15)	(1.21)	(1.21)		
Infl	0.4322**	0.4354**	0.3299**	0.3375**	-3.5811***	-3.5621***
	(2.28)	(2.28)	(2.35)	(2.47)	(-2.80)	(-2.78)
GDPg	-0.3515	-0.3408	-1.4671***	-1.3807***	-3.8125	-3.6697
	(-1.38)	(-1.36)	(-6.54)	(-7.03)	(-1.60)	(-1.61)
StabilityROA_99	0.0408**	0.0408**	-0.0395*	-0.0394*	0.2012	0.2012
	(2.18)	(2.19)	(-1.87)	(-1.87)	(1.07)	(1.08)
Deposits_99			-0.1721***	-0.1711***	0.4444	0.4455
			(-4.91)	(-4.84)	(1.08)	(1.09)
Constant	127.7087***	128.0737***	149.8950***	111.8912***	724.0648***	673.1416**
	(3.30)	(3.41)	(5.27)	(3.98)	(2.73)	(2.48)
Observations	835	835	835	835	835	835
R^2	0.19	0.19	0.31	0.31	0.02	0.02
Adjusted R^2	0.18	0.18	0.30	0.30	0.01	0.01
AIC	5356.02	5356.01	5233.02	5231.97	8950.13	8950.17
BIC	5408.02	5408.01	5289.75	5288.70	9002.13	9002.17

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

4.1.2 Financial Stability

Table 8 presents the regression results for the financial stability variables. Contrary to what was hypothesized, Pix has no effect on the financial stability of Brazilian banks, given the statistically insignificant coefficients. Considering the indirect mechanisms through which financial stability could be affected by Pix, namely financial inclusion and competition, such finding might indicate that Pix has not yet caused sufficient impacts on those indicators to affect the individual stability of Brazilian banks. However, it is important to highlight that financial inclusion and competition measures are not included as variables and further research is required to understand how Pix interacts with such indicators.

Furthermore, as it will be presented in the next subsection, the impact of Pix on the financial stability and risk-taking behaviour of Brazilian banks is significant when considering both groups separately. As previously referred, this is likely related to the increased variance in the complete dataset, which increases the standard errors of the coefficients. In addition, the difference in business models of traditional and digital banks might also indicate different responses to Pix when it comes to financial stability. Therefore, the effect on the overall dataset may be masked by their heterogeneity.

Table 8: Financial Stability Regression Results – Complete Dataset

STABILITY MEASURES – COMPLETE DATASET				
	(1) StabilityROA_99	(2) StabilityROA_99	(3) LLP_99	(4) LLP_99
LnPixVol	**-0.0558** **(-0.15)**		**-0.0362** **(-0.52)**	
LnPixTrans		**-0.0445** **(-0.15)**		**-0.0254** **(-0.46)**
Equity_99	1.5009*** (9.62)	1.5009*** (9.63)	-0.0233 (-0.74)	-0.0234 (-0.74)
FeeIncome_99	-0.0839* (-1.87)	-0.0839* (-1.86)	0.0029 (0.25)	0.0031 (0.27)
Size_99	-7.2119*** (-6.44)	-7.2112*** (-6.46)	1.3274*** (4.49)	1.3231*** (4.50)
Loans_99	0.0561 (1.63)	0.0561 (1.63)	-0.0172 (-1.31)	-0.0171 (-1.31)
LLP_99	-0.0458 (-0.64)	-0.0458 (-0.64)		
CR3	0.7405 (1.16)	0.7421 (1.16)	0.3150* (1.65)	0.3163* (1.66)
CTI_99	0.0050 (1.16)	0.0050 (1.16)	0.0003 (0.10)	0.0003 (0.10)

Deposits_99	0.0748**	0.0748**	0.0331*	0.0331*
	(2.18)	(2.19)	(1.77)	(1.77)
Infl	0.3469***	0.3470***	-0.1377**	-0.1371**
	(3.33)	(3.31)	(-2.45)	(-2.44)
GDPg	-0.1206	-0.1191	0.3071***	0.3099***
	(-0.42)	(-0.43)	(2.93)	(3.06)
Constant	122.9614***	122.3503***	-32.6493***	-33.0381***
	(3.33)	(3.28)	(-3.41)	(-3.51)
Observations	835	835	835	835
R^2	0.41	0.41	0.05	0.05
Adjusted R^2	0.40	0.40	0.04	0.04
AIC	5861.26	5861.26	3863.94	3863.96
BIC	5913.27	5913.27	3915.95	3915.96

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

4.2 Traditional Banks vs Digital Banks

In this subsection, the control variables are omitted from the regression tables so that the comparison between traditional and digital banks is clearer for the reader. The complete regression tables can be found in the Appendix. In addition, I will only refer to the coefficient of *LnPixVol* in the interpretation for the purpose of clarity, provided that *LnPixTrans* causes very similar but slightly smaller effects on the dependent variable, as mentioned previously.

4.2.1 Performance and Transmission Mechanisms

The results in Table 9 indicate that the performance of both traditional and digital banks are negatively impacted by Pix. However, the magnitude of the coefficient differs largely from one to the other. While a 10% increase in Pix financial volume leads to a 0.01 p.p. and 0.06 p.p. decrease in traditional banks' ROA and ROE, respectively, the effect is around five times larger for digital banks (0.04 p.p. decrease in ROA and 0.31 p.p. decrease in ROE). The difference is even more significant considering digital banks have lower median values of ROA (0.05% vs. 0.30%) and ROE (0.47% vs. 3.29%). This finding can be explained by the distinct business models of these two groups. According to Ben Naceur (2023), the larger size and wider geographical coverage of commercial banks may provide them with advantages and better resources to withstand shocks, like the one caused by the introduction of Pix. Moreover, Schapiro et al. (2023) notes that as "multiple banks", Brazilian incumbent financial institutions are involved in a wide variety of financial products and services, including credit, payments, asset management, insurance and pension plans, giving them a more stable and mixed source of income.

However, the impact on NIM is larger on traditional banks than on digital banks, as a 10% increase in the financial volume of Pix leads to a 0.03 p.p. decrease in the NIM of the first group, and to a 0.02 p.p. decrease in the second group. The analysis of the transmission mechanisms, shown in table 10, might help understand such a difference. Differently from the observed in the complete dataset, the effect of Pix on banks' deposits is significant when the two types of institutions are considered separately. More specifically, a 10% increase in Pix financial volume leads to 0.18 p.p. increase in the deposit ratio of traditional banks, and to a 0.13 p.p. decrease in that of digital banks. Given the opposite effects between each other, it might be possible that they were cancelled out in the complete dataset regression results.

A potential explanation for these results can also be found with Chen et al. (2019) as they showed that the emergence of TPPs resulted in a partial split of deposits from the banking sector, making banks increase their interest rates to attract depositors, at the expenses of their NIMs. A key difference here is that Pix is fully integrated with banks, meaning that every amount transacted through Pix is associated with a deposit in a participant bank. Therefore, an outflow of funds from the system seems unlikely. In this manner, one possible interpretation of this coefficients is that Pix has led to a flow of deposits from digital to traditional banks. As noted by Arnold and Jeffrey (2016), digital banks and FinTechs' attractive business models often rely on the offering of improved value through lower pricing. In terms of payment services, such institutions attracted depositors by providing efficient, safe, quick and low-cost solutions. However, after the launch of Pix, a faster, safer and costless solution was available for depositors of any bank. Thus, as payment services ceased to be a competitive advantage of digital banks, depositors might have had an incentive to move their funds from newly established digital banks towards safer, more stable and reputable financial institutions.

Moving to Fee Income, the results show that Pix's impact is larger on traditional banks. A 10% increase in financial volume leads to a 0.35 p.p. decrease in their Fee Income to total income ratio, whereas for digital banks, the decrease is 0.23 p.p. However, despite the larger coefficient for traditional banks, it is important to consider the difference in revenue diversification between the two groups. The median Fee Income value for traditional banks represents only 6.5% of total revenues, whereas for digital banks it accounts to 16%. This difference in revenue composition helps explain why Pix has a greater impact on the performance indicators of digital banks.

Finally, while Pix had no significant impact on the cost-to-income ratios of traditional banks, the effect is significant at the 10% level for the digital banks. The estimation suggests that a 10% increase in the financial volume of Pix leads to a 1.54 p.p. improvement in the cost-to-income ratio of digital banks. A possible explanation is that with Pix being operated by the Central Bank, costs associated with payment processing infrastructure are being relieved. The effect is only seen in digital banks possibly due to the larger relevance of payment services in their business model, as argued above, meaning that cost efficiency gains associated with such service might be more impactful in the banks' overall cost structure. However, the effect is not very meaningful considering the median value of digital bank's CTI of 98%.

Overall, the findings suggest that Pix has had a stronger negative effect on digital banks than on incumbent financial institutions. This is mainly attributed to their difference in business models and risk factors, where incumbent financial institutions have a more diversified source of revenue, are less reliant on fee income and offer a safer structure for depositors.

Table 9: Performance Regression Rresults – Traditional vs Digital Banks

	PERFORMANCE MEASURES – TRADITIONAL VS DIGITAL BANKS						
		(1)	(2)	(3)	(4)	(5)	(6)
		ROA_99	ROA_99	NIM_99	NIM_99	ROE_99	ROE_99
Traditional Banks	**LnPixVol**	**-0.085***** **(-3.23)**		**-0.339***** **(-8.28)**		**-0.638***** **(-2.67)**	
	LnPixTrans		**-0.067***** **(-3.13)**		**-0.271***** **(-8.61)**		**-0.494**** **(-2.49)**
	Observations	543	543	543	543	543	543
	Adjusted R^2	0.12	0.12	0.26	0.26	0.10	0.10
Digital Banks	**LnPixVol**	**-0.417***** **(-5.31)**		**-0.171**** **(-2.32)**		**-3.263**** **(-2.52)**	
	LnPixTrans		**-0.342***** **(-5.38)**		**-0.136**** **(-2.24)**		**-2.748***** **(-2.67)**
	Observations	292	292	292	292	292	292
	Adjusted R^2	0.26	0.26	0.20	0.20	0.12	0.12

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

Table 10: Transmission Mechanisms Regression Results – Traditional vs Digital Banks

TRANSMISSION MECHANISMS – TRADITIONAL VS DIGITAL BANKS							
		(1) Deposits_99	(2) Deposits_99	(3) FeeIncome_99	(4) FeeIncome_99	(5) CTI_99	(6) CTI_99
Traditional Banks	**LnPixVol**	**1.885*** (2.73)**		**-3.681*** (-13.20)**		**-1.357 (-1.27)**	
	LnPixTrans		**1.535*** (2.86)**		**-2.940*** (-13.51)**		**-1.081 (-1.27)**
	Observations	543	543	543	543	543	543
	Adjusted R^2	0.26	0.26	0.32	0.32	0.01	0.01
Digital Banks	**LnPixVol**	**-1.376** (-2.29)**		**-2.4278*** (-4.80)**		**-16.178* (-1.82)**	
	LnPixTrans		**-1.116** (-2.34)**		**-1.9514*** (-4.74)**		**-12.897* (-1.81)**
	Observations	292	292	292	292	292	292
	Adjusted R^2	0.35	0.35	0.29	0.29	0.03	0.03

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

4.1.2 Financial Stability

Table 11 shows the estimations for the financial stability indicators for traditional and digital banks. All coefficients are statistically significant at the 1% level. The results indicate that the insolvency risk of both traditional and digital banks, captured by the Z-Score, is negatively impacted by Pix, as opposed to the hypothesis. A 10% increase in the financial volume of Pix leads to a 0.10 p.p. decrease in the Z-Score of traditional banks, whereas the decrease for digital banks is of 0.20 p.p. Similarly to the impacts on performance, digital banks are far more sensitive to Pix than incumbent financial institutions. For traditional banks, the impact on the Z-Score is not very significant considering the high median value of 76.6. That is not the case for digital banks, who have considerably lower Z-Scores, with a median value of 15.5.

As previously discussed, the negative effect of Pix on the performance indicators of Brazilian banks may indicate increased competitive pressure introduced by a new player in the payment market. This pressure could reduce revenue diversification and increase competition for deposits, leading to higher interest expenses. Accordingly, the negative impact on financial stability can be explained by the findings of Leroy and Lucotte (2017) and Saif-Alyousfi et al. (2020), who demonstrated that heightened competition among banks negatively affect their Z-Scores, mainly through reducing income stability and increasing costs.

In terms of LLP, likewise the effect on deposits, we note opposite impacts of Pix between the two groups. While a 10% increase in Pix's financial volume results in a 0.04 p.p. decrease on the ratio of loan loss provisions to total loans of traditional banks, for digital banks it leads to a 0.07 p.p. increase, indicating a worsening of credit quality for the second group. Chen et al. (2019) showed that banks increased their risk-taking behaviour in the presence of TPPs, evidenced by higher NPL ratios. As the observed impact of Pix on digital banks' performance is significantly higher, it is possible that those institutions are more likely to increase the riskiness of their loans to compensate the losses of revenues associated with Pix. For traditional banks, however, given the smaller impact on profitability, there is less incentive to increase risk-taking.

Overall, the results support the notion that Pix is intensifying competition in the Brazilian banking sector, with digital banks being the most adversely affected due to their heavy reliance on payment services for their business model and revenue streams. Contrary to the initial hypothesis, any potential positive effect of Pix on financial inclusion was insufficient to offset the reduced revenue stability and higher interest expenses that contributed to the lower Z-Scores.

Table 11: Financial Stability Regression Results – Traditional vs Digital Banks

STABILITY MEASURES – TRADITIONAL VS DIGITAL BANKS					
		(1) StabilityROA_99	(2) StabilityROA_99	(3) LLP_99	(4) LLP_99
Traditional Banks	**LnPixVol**	**-1.064*** (-3.09)**		**-0.458*** (-4.32)**	
	LnPixTrans		**-0.844*** (-2.97)**		**-0.363*** (-4.50)**
	Observations	543	543	543	543
	Adjusted R^2	0.61	0.61	0.13	0.13
Digital Banks	**LnPixVol**	**-2.065*** (-3.15)**		**0.756*** (3.93)**	
	LnPixTrans		**-1.681*** (-3.21)**		**0.610*** (4.06)**
	Observations	292	292	292	292
	Adjusted R^2	0.19	0.19	0.05	0.05

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

5. Discussion and Conclusion

The digital revolution in financial services in the recent years has been subject of many discussions among academics and policymakers, with innovations in payment services being at the forefront of this transformation. How such innovations interact with the performance and stability of banks has been a notorious concern within academia. However, as the development of fast or near instant payment systems is a relatively recent trend among countries and central banks, the empirical literature on the topic is notably scarce. This paper seeks to address this gap by examining how Pix, the Central Bank of Brazil's IPS, impacts the performance and stability of Brazilian banks by performing a fixed effects estimation on a panel dataset of 73 financial institutions (comprising 43 traditional and 27 digital banks) over a period of 12 quarters, from 4Q2020 to 3Q2023.

The theoretical framework of this paper considered studies that approached payment innovations in two distinct manners: (i) bank owned and developed instruments such as ATMs, POS terminals, credit/debit cards and e-money (Ardizzi et al., 2019; Hasan et al., 2012; Kasri et al. 2022; Saroy et al., 2023) and (ii) FinTechs and TPPs financial volume (Ben Naceur et al., 2023; Chen et al. 2019). While the studies in the first group show a positive association between digital payments and bank performance and stability indicators, the second indicates a negative relationship as a result of increased competition in the banking sector.

Consistent with the findings of Ben Naceur et al. (2023) and Chen et al. (2019), my results show that higher financial volumes and number of transactions via Pix leads to a decrease in the performance of Brazilian banks, primarily through lowering fee incomes and net interest margins of participant institutions. Similarly, Pix leads to a deterioration in the insolvency risk of Brazilian banks, given its negative effect on the individual Z-Scores. These findings suggest that Pix acts more like a new entrant in the payments market, intensifying competition, reducing income stability and potentially increasing interest expenses as banks compete for deposits.

In addition, studying the heterogeneity among traditional and digital banks, my results show that the effects of Pix on both performance and stability measures are much larger on the second group. This is mostly attributed to business model differences between the two: while traditional banks in Brazil have a well-diversified income as they operate in a wide range of financial products and services, digital banks are highly reliant on fee incomes stemming from payment services. As a result, Pix offers little risk to incumbent banks and a considerable one to FinTechs.

Finally, my results present interesting implications for policymakers and financial institutions. For central banks, the development and implementation of IPSs could be an effective way to foster competition in the banking sector, although it might pose a risk to the stability of digital banks and FinTechs that are highly reliant on fee incomes that stems from payment services. In addition, the findings suggest that the presence of free-to-use IPSs that are fully integrated with the main banks in the country might eliminate competitive advantages originally held by digital banks, which was a factor to attract deposits in the first place. Therefore, such institutions should invest in the development and expansion of new products and services that provide greater revenue diversification.

5.1 Limitations and Future Research

Nonetheless, the results should be considered in light of the limitations of this research. Firstly, despite the rapid adoption of Pix in Brazil, the period considered is relatively short. Most studies cover larger periods, with yearly instead of quarterly data. Future research could extend the analysis over more years to observe the long-term effects of CB's IPSs on banking financial indicators.

Secondly, although the computation of Z-Score using the standard deviation of ROA over the sample period follows Hasan et al. (2012), most studies use a three-year rolling window, as it provides a more accurate assessment of insolvency risk, especially in unbalanced panel datasets (Leroy and Lucotte, 2017). This approach was not possible due to data limitations.

Thirdly, some of the regression estimations have noticeably low adjusted R-squared values, namely the ones that included CTI and LLP as dependent variables. This might indicate that the general models used for performance and stability might not have a good explanatory power to every dependent variable this paper used. Future research should consider designing a specific model for each of the dependent variable to achieve more reliable estimations.

Fourthly, given the lack of official classification of digital banks by the BCB, I classified banks based on their marketing communication strategy, i.e. whether they market themselves as a "digital bank" in their official websites. More appropriate classification criteria such as the level of technology in the bank's operations, the share of accounts opened digitally, and the number of physical branches, were not used due to data unavailability. Future research on the heterogeneity of digital and traditional banks could implement these classification criteria.

Finally, although the findings suggest an increased competition as a result of Pix implementation, specific measures of bank competition and market power, such as the Lerner Index, were not included due to data limitations. The same applies to financial inclusion metrics. Therefore, future research could be done to measure the effect of Pix and other central bank-developed IPSs on such indicators, as they stand at the core of the CB's objectives.

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7. Appendix

Table A 1: Performance Regression Results – Traditional Banks

PERFORMANCE MEASURES – TRADITIONAL BANKS						
	(1) ROA_99	(2) ROA_99	(3) NIM_99	(4) NIM_99	(5) ROE_99	(6) ROE_99
LnPixVol	**-0.0849*** (-3.23)**		**-0.3386*** (-8.28)**		**-0.6378*** (-2.67)**	
LnPixTrans		**-0.0666*** (-3.13)**		**-0.2710*** (-8.61)**		**-0.4938** (-2.49)**
Equity_99	0.0500*** (3.28)	0.0499*** (3.25)	0.0784*** (2.71)	0.0792*** (2.74)	0.0870 (0.72)	0.0845 (0.69)
FeeIncome_99	-0.0005 (-0.14)	-0.0005 (-0.14)	-0.0285*** (-3.65)	-0.0286*** (-3.67)	0.0192 (0.61)	0.0198 (0.62)
Size_99	0.4839*** (3.47)	0.4824*** (3.45)	0.0970 (0.28)	0.1067 (0.31)	3.9172*** (4.03)	3.8855*** (3.94)
Loans_99	0.0046*** (3.14)	0.0046*** (3.12)	0.0169*** (2.88)	0.0169*** (2.87)	0.0005 (0.03)	0.0007 (0.04)
LLP_99	-0.0338*** (-2.66)	-0.0337*** (-2.66)	-0.0900*** (-2.64)	-0.0900*** (-2.64)	-0.4728** (-2.11)	-0.4718** (-2.11)
Deposits_99	0.0008 (0.23)	0.0008 (0.23)	-0.0076 (-0.94)	-0.0074 (-0.92)	-0.0115 (-0.41)	-0.0116 (-0.41)
CR3	-0.0611 (-1.61)	-0.0585 (-1.49)	0.0470 (0.84)	0.0568 (1.21)	-0.6935** (-2.04)	-0.6742* (-1.91)
CTI_99	-0.0005 (-0.59)	-0.0005 (-0.59)	-0.0012 (-0.76)	-0.0012 (-0.76)	-0.0028 (-0.20)	-0.0028 (-0.20)
Infl	-0.0068 (-0.57)	-0.0064 (-0.53)	0.0048 (0.14)	0.0056 (0.16)	-0.0148 (-0.13)	-0.0114 (-0.10)
GDPg	-0.0279 (-1.54)	-0.0251 (-1.40)	-0.0974*** (-4.21)	-0.0891*** (-4.23)	-0.3405* (-1.69)	-0.3161 (-1.57)
StabilityROA_99	0.0026 (1.34)	0.0026 (1.34)	0.0018 (0.38)	0.0018 (0.38)	0.0383*** (2.75)	0.0384*** (2.75)
Constant	-3.6830 (-1.27)	-4.5910 (-1.45)	4.0827 (0.72)	0.2858 (0.05)	-15.6952 (-0.73)	-22.2884 (-0.95)
Observations	543	543	543	543	543	543
R^2	0.14	0.14	0.27	0.28	0.12	0.12

Adjusted R^2	0.12	0.12	0.26	0.26	0.10	0.10
AIC	70.48	72.92	934.91	934.29	2622.47	2622.92
BIC	117.75	124.48	982.17	981.56	2669.74	2670.19

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

Table A 2: Transmission Mechanisms regression results – Traditional Banks

TRANSMISSION MECHANISMS – TRADITIONAL BANKS						
	(1) Deposits_99	(2) Deposits_99	(3) FeeIncome_99	(4) FeeIncome_99	(5) CTI_99	(6) CTI_99
LnPixVol	**1.8852*** **		**-3.6811*** **		**-1.3569**	
	(2.73)		**(-13.20)**		**(-1.27)**	
LnPixTrans		**1.5355*** **		**-2.9398*** **		**-1.0812**
		(2.86)		**(-13.51)**		**(-1.27)**
Equity_99	-2.8736***	-2.8805***	-0.4321*	-0.4232*	1.8658	1.8679
	(-8.73)	(-8.70)	(-1.75)	(-1.71)	(1.65)	(1.65)
FeeIncome_99	-0.2225***	-0.2198***			-0.1125	-0.1128
	(-5.15)	(-5.02)			(-0.44)	(-0.44)
Size_99	-18.5654***	-18.6747***	-2.9736	-2.8723	1.8143	1.8381
	(-5.89)	(-5.89)	(-1.46)	(-1.41)	(0.24)	(0.24)
Loans_99	-0.0428	-0.0423	-0.0308	-0.0308	0.2886	0.2887
	(-0.74)	(-0.73)	(-0.57)	(-0.58)	(1.57)	(1.57)
LLP_99	0.7223***	0.7229***	0.2039	0.2038	1.5490	1.5494
	(3.06)	(3.06)	(1.51)	(1.52)	(1.01)	(1.01)
CR3	0.0544	0.0010	0.9618	1.0672	1.1288	1.1684
	(0.07)	(0.00)	(1.06)	(1.22)	(1.22)	(1.28)
CTI_99	0.0134	0.0134	-0.0062	-0.0062		
	(0.68)	(0.68)	(-0.44)	(-0.44)		
Infl	0.2442*	0.2424*	0.3675**	0.3762**	0.0753	0.0791
	(1.76)	(1.88)	(2.36)	(2.45)	(0.21)	(0.22)
GDPg	0.1067	0.0755	-1.6659***	-1.5722***	-0.7258	-0.6900
	(0.27)	(0.20)	(-5.56)	(-5.76)	(-1.00)	(-0.98)
StabilityROA_99	0.1573***	0.1573***	-0.0515**	-0.0515**	-0.0613	-0.0613
	(7.44)	(7.39)	(-2.01)	(-2.01)	(-0.47)	(-0.47)
Deposits_99			-0.1781***	-0.1759***	0.1943	0.1949
			(-3.13)	(-3.09)	(0.63)	(0.63)

Constant	333.2443***	354.7637***	109.8393***	68.5528*	-18.0820	-33.1297
	(6.86)	(7.16)	(2.96)	(1.83)	(-0.14)	(-0.25)
Observations	543	543	543	543	543	543
R^2	0.28	0.28	0.33	0.33	0.03	0.03
Adjusted R^2	0.26	0.26	0.32	0.32	0.01	0.01
AIC	3396.12	3395.23	3275.22	3274.42	4847.73	4847.73
BIC	3443.38	3442.50	3322.49	3321.69	4895.00	4895.00

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

Table A 3: Financial stability regression results – Traditional Banks

STABILITY MEASURES – TRADITIONAL BANKS				
	(1) StabilityROA_99	(2) StabilityROA_99	(3) LLP_99	(4) LLP_99
LnPixVol	**-1.0638*** **		**-0.4582*** **	
	(-3.09)		**(-4.32)**	
LnPixTrans		**-0.8442*** **		**-0.3626*** **
		(-2.97)		**(-4.50)**
Equity_99	4.1902***	4.1911***	0.1476	0.1478
	(15.84)	(15.80)	(1.48)	(1.48)
FeeIncome_99	-0.0916**	-0.0917**	0.0240*	0.0240*
	(-2.20)	(-2.20)	(1.75)	(1.76)
Size_99	2.3264	2.3348	3.5853***	3.5864***
	(0.60)	(0.60)	(3.70)	(3.69)
Loans_99	0.1624***	0.1625***	-0.0358**	-0.0357**
	(3.48)	(3.48)	(-2.36)	(-2.36)
LLP_99	-0.2739*	-0.2734*		
	(-1.90)	(-1.90)		
CR3	0.9713*	1.0026**	-0.0181	-0.0046
	(1.93)	(2.01)	(-0.21)	(-0.05)
CTI_99	-0.0060	-0.0060	0.0095	0.0095
	(-0.48)	(-0.48)	(0.95)	(0.95)
Deposits_99	0.2239***	0.2243***	0.0599**	0.0600**
	(5.52)	(5.50)	(2.21)	(2.21)
Infl	0.2524	0.2558	-0.0091	-0.0075
	(1.23)	(1.26)	(-0.19)	(-0.15)
GDPg	-0.0629	-0.0330	0.0704	0.0839*

	(-0.41)	(-0.21)	(1.40)	(1.77)
Constant	-48.7768	-60.4608	-49.2090***	-54.2179***
	(-0.88)	(-1.02)	(-2.86)	(-2.92)
Observations	543	543	543	543
R^2	0.62	0.62	0.14	0.14
Adjusted R^2	0.61	0.61	0.13	0.13
AIC	3587.88	3589.90	2077.14	2077.28
BIC	3635.14	3641.47	2124.40	2124.55

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

Table A 4: Performance regression results – Digital Banks

PERFORMANCE MEASURES – DIGITAL BANKS						
	(1)	(2)	(3)	(4)	(5)	(6)
	ROA_99	ROA_99	NIM_99	NIM_99	ROE_99	ROE_99
LnPixVol	**-0.4166*** **		**-0.1712** **		**-3.2624** **	
	(-5.31)		**(-2.32)**		**(-2.52)**	
LnPixTrans		**-0.3422*** **		**-0.1357** **		**-2.7479*** **
		(-5.38)		**(-2.24)**		**(-2.67)**
Equity_99	-0.0937***	-0.0936***	0.0180*	0.0180*	0.9413***	0.9425***
	(-3.67)	(-3.67)	(1.78)	(1.79)	(2.83)	(2.83)
FeeIncome_99	0.0518**	0.0520**	-0.0372***	-0.0372***	0.1972	0.2002
	(2.24)	(2.24)	(-5.27)	(-5.26)	(0.72)	(0.72)
Size_99	1.1986***	1.2193***	-0.1465	-0.1449	14.8474***	15.1036***
	(5.41)	(5.58)	(-0.66)	(-0.64)	(5.90)	(6.04)
Loans_99	-0.0013	-0.0014	-0.0269**	-0.0269**	0.2468	0.2466
	(-0.11)	(-0.11)	(-2.42)	(-2.42)	(1.39)	(1.39)
LLP_99	-0.0960***	-0.0957***	-0.0645***	-0.0645***	-0.6689	-0.6647
	(-2.74)	(-2.75)	(-3.35)	(-3.36)	(-1.08)	(-1.07)
Deposits_99	-0.0299*	-0.0301*	-0.0126	-0.0126	-0.2855*	-0.2882*
	(-1.83)	(-1.84)	(-1.08)	(-1.09)	(-1.89)	(-1.91)
CR3	0.3121*	0.3220**	0.1927	0.1975*	0.1712	0.2390
	(1.84)	(2.06)	(1.64)	(1.68)	(0.06)	(0.09)
CTI_99	-0.0008	-0.0008	0.0010*	0.0010*	0.0007	0.0006
	(-1.46)	(-1.47)	(1.79)	(1.80)	(0.06)	(0.05)
Infl	0.0103	0.0104	-0.0128	-0.0122	-1.2261	-1.2335
	(0.23)	(0.24)	(-0.40)	(-0.38)	(-1.58)	(-1.61)

GDPg	-0.0950	-0.0889	0.0001	0.0050	-0.4399	-0.4245
	(-1.25)	(-1.23)	(0.00)	(0.11)	(-0.36)	(-0.36)
StabilityROA_99	0.0217***	0.0216***	0.0009	0.0009	0.0229	0.0217
	(4.48)	(4.48)	(0.33)	(0.33)	(0.43)	(0.41)
Constant	-21.8161*	-26.3275**	0.0712	-1.7961	-173.8132	-208.9590
	(-1.71)	(-2.30)	(0.02)	(-0.38)	(-1.04)	(-1.36)
Observations	292	292	292	292	292	292
R^2	0.29	0.29	0.23	0.23	0.16	0.16
Adjusted R^2	0.26	0.26	0.20	0.20	0.12	0.12
AIC	939.67	939.11	682.35	684.41	2540.88	2540.61
BIC	980.11	979.55	722.80	728.53	2581.33	2581.05

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

Table A 5: Transmission Mechanisms regression results – Digital Banks

TRANSMISSION MECHANISMS – DIGITAL BANKS						
	(1)	(2)	(3)	(4)	(5)	(6)
	Deposits_99	Deposits_99	FeeIncome_99	FeeIncome_99	CTI_99	CTI_99
LnPixVol	**-1.3758****		**-2.4278*****		**-16.1783***	
	(-2.29)		**(-4.80)**		**(-1.82)**	
LnPixTrans		**-1.1156****		**-1.9514*****		**-12.8972***
		(-2.34)		**(-4.74)**		**(-1.81)**
Equity_99	-0.6533***	-0.6527***	-0.3426***	-0.3421***	-0.7814	-0.7796
	(-5.59)	(-5.58)	(-2.83)	(-2.83)	(-0.49)	(-0.49)
FeeIncome_99	-0.0756	-0.0760			1.6335*	1.6324*
	(-1.34)	(-1.35)			(1.66)	(1.66)
Size_99	2.8401	2.8873	-7.5433***	-7.4778***	37.4002*	37.6560*
	(1.38)	(1.39)	(-6.30)	(-6.16)	(1.85)	(1.85)
Loans_99	-0.3891***	-0.3890***	-0.0870*	-0.0870*	0.2024	0.2017
	(-5.26)	(-5.26)	(-1.77)	(-1.77)	(0.17)	(0.17)
LLP_99	0.0598	0.0605	-0.0686	-0.0678	-0.0465	-0.0439
	(0.93)	(0.93)	(-1.26)	(-1.25)	(-0.04)	(-0.04)
CR3	-0.7916	-0.7564	0.4646	0.5283	-42.5325***	-42.0914***
	(-1.06)	(-1.05)	(1.00)	(1.17)	(-3.54)	(-3.55)
CTI_99	0.0019	0.0019	0.0100	0.0100		
	(0.49)	(0.48)	(1.40)	(1.40)		
Infl	0.2841**	0.2861**	0.2531	0.2588	-6.9089***	-6.8564***

	(2.55)	(2.53)	(1.34)	(1.38)	(-3.22)	(-3.28)
GDPg	-0.3941	-0.3669	-0.9157***	-0.8592***	-14.1776**	-13.7500**
	(-1.37)	(-1.35)	(-3.20)	(-3.26)	(-2.36)	(-2.41)
StabilityROA_99	-0.0147	-0.0150	-0.0032	-0.0035	0.0677	0.0663
	(-0.73)	(-0.74)	(-0.14)	(-0.15)	(0.43)	(0.42)
Deposits_99			-0.1036	-0.1041	0.4246	0.4221
			(-1.19)	(-1.19)	(0.47)	(0.47)
Constant	98.8782***	83.8985**	184.6807***	158.1969***	1955.2604***	1779.0567***
	(2.64)	(2.07)	(8.90)	(7.81)	(2.97)	(2.77)
Observations	292	292	292	292	292	292
R^2	0.37	0.37	0.32	0.32	0.07	0.07
Adjusted R^2	0.35	0.35	0.29	0.29	0.03	0.03
AIC	1851.22	1851.07	1943.15	1943.01	3430.43	3428.44
BIC	1895.34	1895.19	1987.27	1987.13	3474.55	3468.89

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

Table A 6: Financial stability regression results – Digital Banks

STABILITY MEASURES – DIGITAL BANKS				
	(1)	(2)	(3)	(4)
	StabilityROA_99	StabilityROA_99	LLP_99	LLP_99
LnPixVol	**-2.0647***		**0.7562***	
	(-3.15)		**(3.93)**	
LnPixTrans		**-1.6805***		**0.6099***
		(-3.21)		**(4.06)**
Equity_99	0.9402***	0.9402***	-0.0316	-0.0316
	(6.22)	(6.23)	(-0.95)	(-0.95)
FeeIncome_99	-0.0084	-0.0092	-0.0165	-0.0163
	(-0.14)	(-0.15)	(-1.20)	(-1.20)
Size_99	-0.0083	0.0732	-0.2365	-0.2587
	(-0.01)	(0.07)	(-0.43)	(-0.47)
Loans_99	0.0445	0.0444	0.0106	0.0106
	(1.18)	(1.17)	(0.34)	(0.34)
LLP_99	-0.0177	-0.0165		
	(-0.21)	(-0.20)		

CR3	0.1439	0.1952	0.7018	0.6820
	(0.09)	(0.12)	(1.42)	(1.38)
CTI_99	0.0011	0.0011	-0.0001	-0.0001
	(0.44)	(0.43)	(-0.04)	(-0.04)
Deposits_99	-0.0536	-0.0544	0.0198	0.0201
	(-0.76)	(-0.78)	(0.90)	(0.90)
Infl	0.6145	0.6167	-0.3501*	-0.3515*
	(1.28)	(1.28)	(-1.75)	(-1.75)
GDPg	-1.2349**	-1.1968**	0.6429**	0.6262**
	(-2.11)	(-2.13)	(2.56)	(2.59)
Constant	69.2909	46.8715	-42.2646*	-34.0306
	(0.79)	(0.53)	(-1.68)	(-1.34)
Observations	292	292	292	292
R^2	0.22	0.22	0.08	0.08
Adjusted R^2	0.19	0.19	0.05	0.05
AIC	2227.89	2227.78	1525.68	1525.59
BIC	2272.01	2271.90	1566.12	1566.03

*, **, *** indicate the level of statistical significance of the coefficients, respectively at the 10%, 5% and 1% level.

Table A 7: Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) LnPixVol	1															
(2) LnPixTrans	0.999	1														
(3) ROA	0.006	0.006	1													
(4) ROE	0.048	0.047	0.602	1												
(5) NIM	-0.109	-0.110	0.240	0.178	1											
(6) CTI	-0.012	-0.013	-0.455	-0.251	-0.100	1										
(7) FeeIncome	-0.135	-0.137	-0.338	-0.301	-0.142	0.204	1									
(8) Deposits	0.008	0.008	-0.016	-0.111	0.145	0.044	-0.162	1								
(9) StabilityROA	-0.033	-0.033	0.231	0.190	-0.048	-0.230	-0.258	-0.205	1							
(10) LLP	0.043	0.044	-0.029	-0.046	-0.107	0.124	0.074	0.052	-0.167	1						
(11) Equity	-0.017	-0.017	-0.230	0.027	0.145	0.118	0.154	-0.298	0.109	0.037	1					
(12) Size	0.060	0.061	0.225	0.191	-0.269	-0.188	-0.189	-0.288	0.344	0.011	-0.396	1				
(13) Loans	0.001	0.002	0.162	0.132	0.162	-0.044	-0.368	0.155	0.169	0.198	-0.004	-0.029	1			
(14) GDPg	-0.593	-0.576	0.002	-0.031	0.048	-0.033	0.027	-0.009	0.018	0.001	-0.001	-0.015	0.001	1		
(15) Infl	-0.471	-0.471	-0.018	-0.050	0.038	-0.003	0.073	0.010	0.028	-0.045	0.021	-0.036	0.010	0.329	1	
(16) CR3	0.320	0.323	0.015	0.024	-0.018	-0.020	-0.028	-0.013	-0.012	0.029	0.004	0.015	-0.009	-0.394	-0.474	1