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THE IMPACTS OF PIX ON MERCHANT DISCOUNT RATES

Supervisors

Prof. Francesco NICOLI

Candidate

Matheus OLIVEIRA

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The Impacts of Pix on Merchant Discount Rates

Matheus OLIVEIRA

Abstract

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This study quantitatively analyzes the impact of Pix adoption on the pricing of average merchant discount rates (MDR) charged to merchants in the Brazilian acquiring market, focusing on credit and debit functions. The introduction of Pix by the Central Bank of Brazil in November 2020 represented a structural shift in the Brazilian payment system, leading to changes in consumer and merchant behavior. To investigate the effects of Pix on MDR, an econometric model was built using multiple linear regression with quarterly data from 2011 to 2024. The model incorporates control variables for events relevant to the acquiring market during the period, such as the COVID-19 pandemic and the regulation imposing a cap on debit card interchange fees (TIC), in addition to seasonal variables and the basic interest rate (SELIC). The effects of Pix adoption are analyzed through a continuous variable that captures its progression over time, based on previously validated assumptions. The results suggest that the expansion of Pix significantly accelerated the decline in debit MDR, while providing limited evidence of impact on credit MDR. Structural factors such as the pandemic, TIC regulation, and the SELIC rate were also found to influence the behavior of merchant discount rates. The empirical analysis contributes to the understanding of how new payment arrangements impact already consolidated markets, offering insights for companies in the sector to design strategies that are better aligned with the emerging landscape of competition and innovation. In this regard, the proposed model proves useful for industry operators, regulators, and researchers interested in the evolution of the Brazilian financial system.

Keywords: Pix. MDR. Acquiring market. Payment Systems. Electronic Payments. Cards. Regulation.

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Chapter 1

Introduction

1.1 Context

Acquirers, or payment processors, are financial entities responsible for capturing, processing, and settling payments made through credit and debit cards, as well as other electronic means. This process is carried out through a Point of Sale (POS) terminal. Which is provided by the acquirer itself. An example of POS is shown in Figure 1.1. The main role of the acquirer is to serve as an intermediary between merchants, card networks (like Visa and Mastercard), and issuers (the banks that provide the cards to customers). Acquirers ensure the security of transactions, process payments, and transfer the sale proceeds to merchants, usually charging a fee for the service, known as MDR (Merchant Discount Rate).

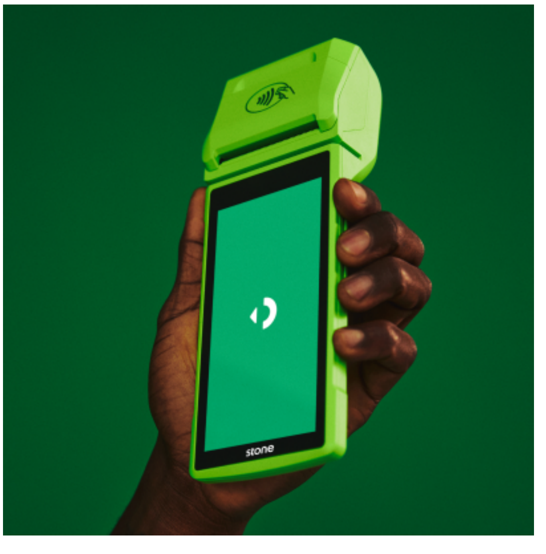

Figure 1.1: Example of a POS machine from acquirer Stone (Source: [1])

In 2010, the Central Bank of Brazil (BCB) and the Administrative Council for Economic Defense (CADE) introduced important measures to end the exclusivity agreements between acquirers and card brands. From that point on, any POS device could process multiple card networks, paving the way for new players to enter the market [2]. This increased competition led to what became known as the *"POS War"* (translated from “Guerra das Maquininhas”) in Brazil, marked by a battle for market share based on pricing and operational efficiency, which gradually squeezed profit margins in the sector [3].

Over time, significant innovations were introduced into the payments market, including the popularization of mobile card machines, the development of wireless and Bluetooth technologies, and the integration of other financial and banking services. This expanded the accessibility of payment acceptance for small and medium-sized businesses, further accelerating the digitalization of the sector.

In this context, Pix emerged as a disruptive innovation within Brazil’s payment system. Officially launched in November 2020 by the Central Bank, Pix was implemented to provide the population with a new transaction model that is accessible, instantaneous, and low-cost. The project was the result of years of planning and regulation by the Central Bank, with the main goals of modernizing the national financial system, reducing the use of cash, fostering market competitiveness and efficiency, and promoting financial and digital inclusion [4].

Pix stands out in Brazil’s payment ecosystem as an innovative 24/7 system that allows real-time transactions at no cost for individuals. It also integrates with various features like QR code payments, scheduling, and installment options. Unlike traditional payment methods like wire transfers (TED, DOC), cards, or “boletos” (bank slips), Pix enables instant transfers with fewer intermediaries, boosting efficiency and reducing transaction costs [5].

Since its launch, Pix has seen rapid adoption by the public. Within a few months, millions of Brazilians were using it in their daily routines for peer-to-peer transfers, business payments, and even tax contributions. Its penetration was driven mainly by its free access, ease of use, speed, and availability, as well as strong support from financial institutions and a favorable regulatory environment promoted by the Central Bank [4]. New features have been gradually introduced, making Pix an increasingly complete payment method. By 2024, it had become the most widely used payment system in the country, handling R$ 26.455 trillion in transactions and accounting for 48% of all payment operations nationwide [6].

1.2 Motivation

The accelerated growth of Pix raises questions about the future of the acquiring market. The fact that it is free for individuals and low-cost for companies makes room for Pix to reduce merchants’ and retailers’ dependence on POS devices, putting at risk the main source of revenue in this sector, the MDR fees, and forcing its players to rethink their strategies beyond transaction processing. In this scenario, the diversification of the banking service portfolio, credit offerings, integration of financial flows, and digital efficiency become even more relevant to ensure the competitiveness of acquirers. Industry specialists, such as Edson Santos [7], have already commented on the topic:

The card payments industry, which for decades grew at double-digit rates,

> *is facing its toughest stress test [Pix]. Between 2009 and 2024, the sector expanded at an average annual rate of 17%, driven by the replacement of cash and checks. Now, however, the sector shows clear signs of slowing down. [...] This slowdown not only reduces expansion opportunities but also puts direct pressure on margins and the valuation of companies in the sector, especially those listed on the stock exchange.*

Additionally, as highlighted by Perez and Bruschi [2], in 2017, a regulatory flexibilization sanctioned by former president Michel Temer allowed businesses to charge different prices for different payment methods. This fact allows for even deeper impacts of Pix on the competitive structure of the Brazilian payments sector, giving merchants the power to pass on transaction costs arising from more expensive payment methods.

Studies such as those by Rocha [8], [9], and by the Central Bank of Brazil itself [4], have already analyzed Pix's influence on the behavior of users within the financial system, as well as impacts on other payment methods, such as credit, debit, TED, and DOC. However, its impact on the acquiring sector has not yet been widely studied and estimated at the academic level, remaining subject to speculation and qualitative analyses of recent developments in the sector.

1.3 Objective

This study aims to deepen that discussion by quantitatively analyzing the impact of Pix on the fees charged by acquirers for their transaction processing services. Thus, the question this study seeks to answer is: **"Does Pix actually influence the reduction of the Merchant Discount Rate, putting the sector's revenues at risk?"**

Based on the historical penetration of Pix in the country and the evolution of the MDR, it will be possible to assess how this phenomenon is reshaping competitiveness in the sector, providing insights into the future of this market and serving as a basis for financial institutions to develop more assertive strategies in their pursuit of market penetration and portfolio innovation that go beyond mere price competition. As stated by Edson Santos [7]:

> *[...] What will define the future is not just the technology itself, but the companies' ability to adapt. For visionary companies, this is the time to innovate and lead. For those who hesitate, the time for adaptation is running out.*

Chapter 2

The Acquiring Market

The Brazilian acquiring market has undergone profound changes over the past decades, driven by technological advances, regulatory developments, as well as the growing role of electronic payments in the economy. The role of acquirers, historically focused on the capture and settlement of card transactions, has evolved in response to increasing competition and the emergence of alternative payment solutions. This chapter aims to present the market structure, its historical background in the national context, as well as the main indicators that define its current functioning. Such contextualization is essential for understanding the mechanisms that determine the formation of the discount rates paid by merchants (MDR), as well as the competitive dynamics which, in turn, may have been affected by Pix.

2.1 The Acquiring Market Structure

The structure of the acquiring market in Brazil is composed of a network of relationships between financial institutions, technology companies, regulatory bodies, and users. This network is organized through payment arrangements, which are regulatory and operational structures responsible for defining the set of rules and technical procedures that allow electronic payments to be carried out. Some examples of payment arrangements include: credit, debit, and prepaid card payments; instant payments (Pix); and "boleto" [10]. The definition of these arrangements has been regulated by the Central Bank of Brazil since the enactment of Law No. 12.865/2013, as described by Ragazzo [11]:

> *Law 12.865/13 was a true milestone for the Brazilian payments market, being responsible for regulating payment arrangements and defining the institutions that are part of the Brazilian Payments System (SPB), in addition to establishing the authority of the BCB and the National Monetary Council (CMN) to regulate and supervise institutions. This law was followed by a series of infra-legal rules that address the regulation of various variables and market failures identified in the sector.*

The processing of a transaction within the card payment arrangement involves the coordinated participation of several agents, which include [12] [13] [3]:

- Cardholder: The consumer who uses their card (credit, debit, or prepaid) to make purchases or payments. Using their card, they are able to purchase goods or services, which are debited directly from their bank account.
- Merchant (Retailer): The business that accepts payment via card and, through a payment terminal, enables the electronic transaction. After the transaction, the merchant receives the net amount, discounting the fees agreed upon with the acquirer.
- Card Network: Representing their respective payment arrangements (such as Visa, Mastercard, and Elo), the networks establish technical and operational rules for the acceptance, processing, and settlement of transactions, and also define the various fees charged throughout the financial flow.
- Issuer: The bank or payment institution responsible for issuing the cards, as well as for defining credit limits. This entity is responsible for charging the purchases made by the cardholder, assumes the credit risk, and earns revenue from annual fees or possible usage fees, in addition to a share of the MDR, charged as an interchange fee (TIC).
- Acquirer: These entities manage relationships with merchants, providing the infrastructure (POS) for transaction capture and communication with the other entities in the system, ensuring processing and financial settlement, and receiving as revenue a portion of the total MDR charged to merchants.

A simplified model of this relationship between agents can be seen in Figure 2.1. When making a purchase, the cardholder initiates the transaction. The merchant, in turn, activates the payment terminal, which sends the request to the acquirer. The acquirer then connects to the card network (such as Visa, Mastercard, or Elo), which in turn contacts the card issuer (usually a bank) responsible for approving or denying the transaction based on available balance or credit limit. This exchange of information among entities occurs within seconds and results in the approval of the transaction by the acquirer. Once approved, the transaction is recorded and proceeds to clearing and settlement, processes that involve transferring the funds to the merchant, minus the applicable fees [14] [12].

There may also be another participant in this flow, known as sub-acquirers (or payment facilitators). Sub-acquirers operate within this network by providing platforms that allow merchants to accept a given payment method, such as cards, but do not directly process or settle these transactions. To do so, they rely on integrating with other acquirers. Examples of such entities in Brazil include PayPal, SumUp, and Mercado Pago [12].

This is an example of how an open-loop transaction processing scheme works (illustrated in Figure 2.2), such as those currently operated by Visa and Mastercard, in which there are multiple issuers and acquirers operating independently. This allows for greater interoperability and competition among agents. This scheme is

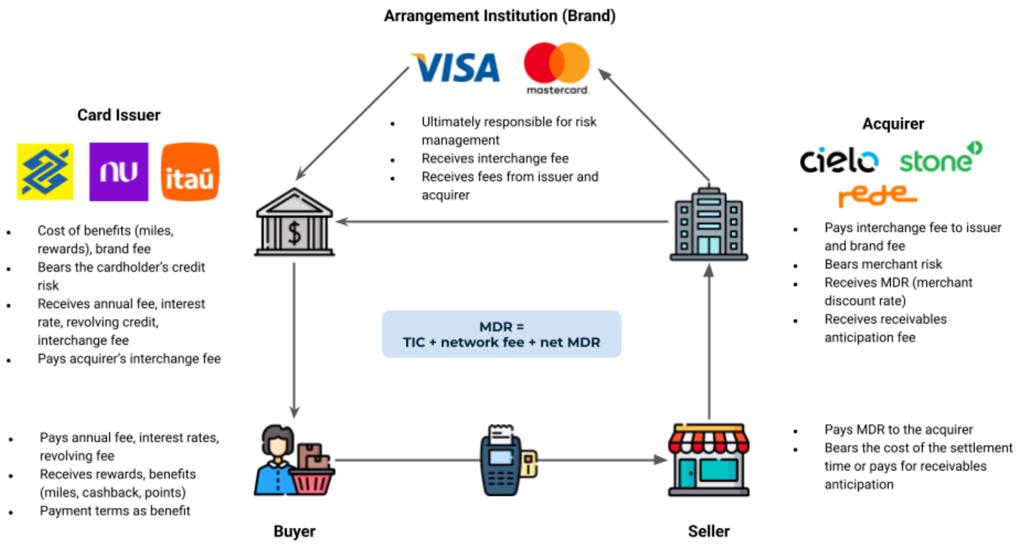

Figure 2.1: Relationship between the agents in an open-loop payment card scheme (Source: Adapted from [15])

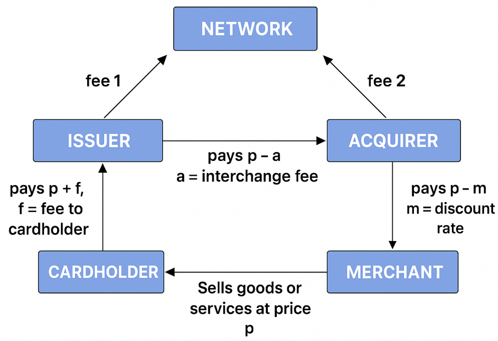

Figure 2.2: Open-loop model of the card payment industry (Source: Adapted from [16])

also referred to as a four-party model, as it distinguishes between the issuer and the acquirer entities, as well as the cardholder and the merchant [2] [12] [13].

There are also the so-called closed-loop schemes (illustrated in Figure 2.3), such as store cards or loyalty programs, which are characterized by a single entity assuming both the roles of issuer and acquirer, centralizing control of the operations. This scheme is also referred to as a three-party model, as it involves only three main entities: cardholder, merchant, and issuer/acquirer. Examples of this model include companies like American Express and Diners, which maintain a more vertically integrated system [2] [12] [13].

The Merchant Discount Rate (MDR), represents the amount charged to merchants for each card transaction. The MDR is divided among the different agents in the system. Part of it goes to the interchange fee (TIC), paid by the acquirer to the card issuer, which compensates for the risks and costs of the credit or debit operation. Another portion is passed on to the card network, which receives a fee known as the

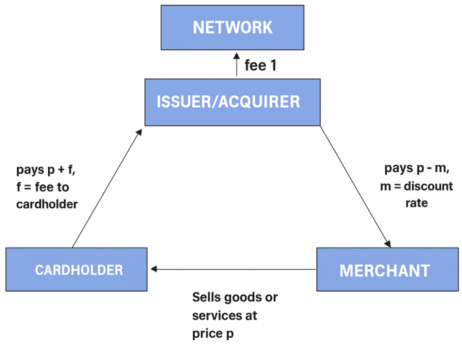

Figure 2.3: Closed-loop model of the card payment industry (Source: Adapted from [16])

assessment fee, used to maintain the technological infrastructure, define operational rules, and manage the global acceptance network. Finally, the acquirer also retains a portion of the MDR, known as the net MDR, to fund its payment processing services [2] [14] [12] [13].

The final composition of the discount rate can be illustrated by the following formula:

$$\textbf{MDR} = \textbf{network fee} + \textbf{TIC} + \textbf{net MDR}$$

Thus, the MDR functions as an aggregated fee, distributed among the key players in the system according to their roles and responsibilities.

2.2 Historical Background of the Acquiring Market in Brazil

The origins of credit cards in Brazil date back to the 1950s, when some establishments, mainly targeting high-income customers, began accepting this form of payment. The first credit card used in the country was Diners Club (an example of which can be seen in Figure 2.4), introduced in 1956 and initially accepted only at a limited selection of restaurants and hotels. Later, in 1968, the bank Bradesco established a partnership with BankAmericard, future Visa, and launched the Elo card, the first credit card issued by a Brazilian bank [17].

In the early years of credit card operations, the process was entirely manual, with no use of any electronic systems such as a point of sale. To carry out a transaction, establishments used imprinting devices, illustrated in Figure 2.5, which worked as follows: by sliding a moving piece, the vendor would print the card data onto a slip of carbon paper, which served as the payment receipt. This slip had to be signed by the customer so that the establishment owner could later send it to the card operator to request reimbursement. This method was slow and prone to fraud, due to the lack of real-time information about the customer's balance and the authenticity of the transaction [19].

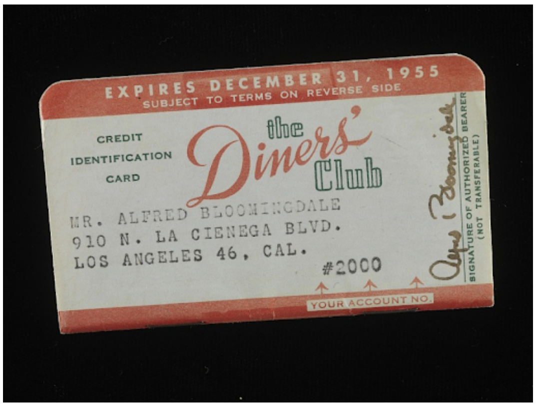

Figure 2.4: Example of one of the first versions of Diners Club in the United States (Source: [18])

Figure 2.5: Printing device used to complete card transactions (Source: [19])

The 1970s were marked by important technological advances in the card processing sector. In 1971, IBM launched the IBM 360 electronic system, which enabled card reading through a magnetic stripe. Two years later, the first electronic transaction authorization system was created in the United States, connecting merchants to a database managed by the acquirer. In 1977, Norway saw the emergence of the first wireless payment terminal, developed by Telenor Mobile, allowing vendors and merchants to accept transactions at mobile points of sale [20].

Despite these advances, by the mid-1990s the acquiring market was still not fully consolidated in Brazil. During that period, the institutions responsible for performing the role of acquirer were the issuing banks themselves, which made operations extremely inefficient, as each bank needed to maintain its own structure for payment acceptance and transaction settlement. In addition, the high inflation and economic downturn experienced during the 1980s also held back the development of this sector [3].

It was only in the second half of the 1990s, with the entry of Visanet and Redecard into the market, along with the economic stability brought about by the Real Plan (1994), that electronic terminals began to truly gain popularity in Brazil. [3].

In its early years of consolidation, the Brazilian acquiring market developed in a concentrated manner. Visanet (later Cielo), founded by Bradesco and Banco do Brasil in 1995, held exclusive rights to process transactions for the Visa network, while Redecard, created by Citibank, Itaú, and Mastercard in 1996, held exclusivity over Mastercard and Diners Club. This lack of interoperability restricted competition between platforms, so that Visa and Mastercard did not compete directly for merchants, effectively forcing them to have terminals from both companies in order to accept card payments from their customers. In practice, the market was characterized by a dual monopoly, in which each card network controlled a share of the card market through its exclusive acquirer [2] [3] [14].

Despite that, the network power and infrastructure of these platforms led to a period of significant expansion for the market, allowing for the mass adoption of cards as a means of payment in Brazil throughout the 2000s. In 2008, both companies together controlled 97.67% of the debit card market and 90.58% of the credit card market [3].

This configuration remained until the early 2010s, when the regulatory institutions overseeing payment systems in Brazil began to intervene in order to promote greater competition and interoperability in the sector. In 2006, the Central Bank of Brazil (BCB), the Secretariat for Economic Law (SDE), the Secretariat for Economic Monitoring (SEAE), and the Ministry of Justice joined efforts to conduct technical studies on the payments market. This working group led to the publication of the "Report on the Payment Card Industry" [21], which identified several flaws in the structure of payment systems in the country [15]. Around the same time, the Central Bank began requiring greater transparency from card networks regarding their commercial practices, expanding the level of information accessible to acquirers [2].

It was then, in July 2010, that both Visa and Mastercard, under regulatory and antitrust pressure, ended their exclusivities with Cielo and Rede, signing Terms of Commitment to Cease (TCC) that allowed any acquirer to capture transactions carried out on their networks [15]. This market liberalization gave merchants greater freedom to choose their acquirer and enabled the entry of new competitors, marking the end of the duopoly finally [2].

Next, Congress approved the Regulatory Framework for Payment Arrangements (Law No. 12,865/2013), which established the supervision of payment methods by the Central Bank of Brazil. The law and its regulations imposed full interoperability in payment arrangements, standardized processes, and granted the Central Bank powers to authorize and oversee acquirers and card networks [15] [2].

The practical effects of these measures soon reflected in the structure and behavior of the acquiring market. As can be seen in Figure 2.6, between 2009 and 2010, the number of acquirers jumped from 5 to 9 [14]. Throughout the 2010s, companies like Stone, PagSeguro, and other fintechs began entering the market, competing directly with traditional acquirers. By 2020, there were already more than 25 acquirers and 200 sub-acquirers operating in the country. During this period, Cielo, Rede, Getnet, Stone, and PagSeguro together held now 88.8% of the market share altogether [3].

Subsequently, other important regulations were established by the Central Bank of Brazil and CADE to maintain the sector's competitiveness. In 2017, CADE approved

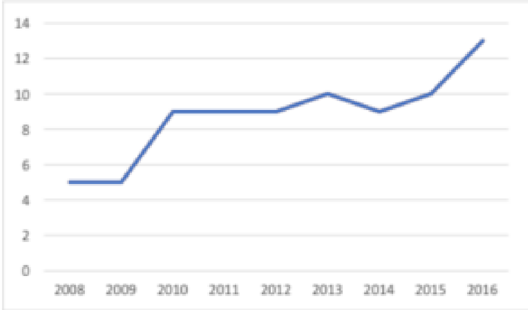

Figure 2.6: Evolution of the number of acquirers in Brazil from 2008 to 2016 (Source: [14])

terms of commitment (TCCs) with Cielo, Elo, Itaú Unibanco, Rede, and Hipercard to end anticompetitive practices in the electronic payments market. The TCCs with Cielo and Elo ended the exclusivity between the Elo brand and the acquirer Cielo, as well as the use of Pinpad devices between Cielo and Rede. The TCCs with Itaú/Rede/Hipercard ended the exclusivity between the Hipercard brand and the acquirer Rede (both part of the Itaú group) and allowed the insertion of competitors' cryptographic keys into Rede's Pinpads, promoting greater interoperability [2]. In the same year, Law 13.455/17 began to allow commercial establishments to charge different prices for different payment methods. This set a precedent for sellers to pass acceptance service costs, such as the merchant discount rates, onto their customers, encouraging them to choose cheaper payment methods [2].

Another important regulation was Circular No. 3.887, issued by the Central Bank of Brazil in March 2018, and in effect since October 1st of that year. This circular established two maximum limits for the Interchange Fee (TIC) on debit card transactions: (i) 0.5% as a weighted quarterly average by transaction value, and (ii) 0.8% as the maximum value per transaction [22]. This structure was maintained by Circular No. 4.020/2020 [23] and later by BCB Resolution No. 246/2022, which consolidated existing regulation and added a new specific limit for prepaid card TIC, set at 0.7% per transaction [24].

This history of developments and regulations in Brazil's acquiring sector can be seen summarized in Figure 2.7 and demonstrates the efforts of regulatory institutions, such as the Central Bank of Brazil and CADE, to ensure interoperability and competitiveness in the sector, providing fairer negotiation conditions among its agents.

2.3 The Brazilian Acquiring Market in Numbers

Brazil's payment card market has shown consistent growth in recent years, as illustrated in Figures 2.8 and 2.9. Over a 10-year period, from the second quarter of 2014 to the second quarter of 2024, the number of active cards rose from 77.3 million to 221.2 million (an increase of 186%) for credit, and from 92.9 million to 162.1 million (an increase of 74.5%) for debit. In addition, the total transaction volume

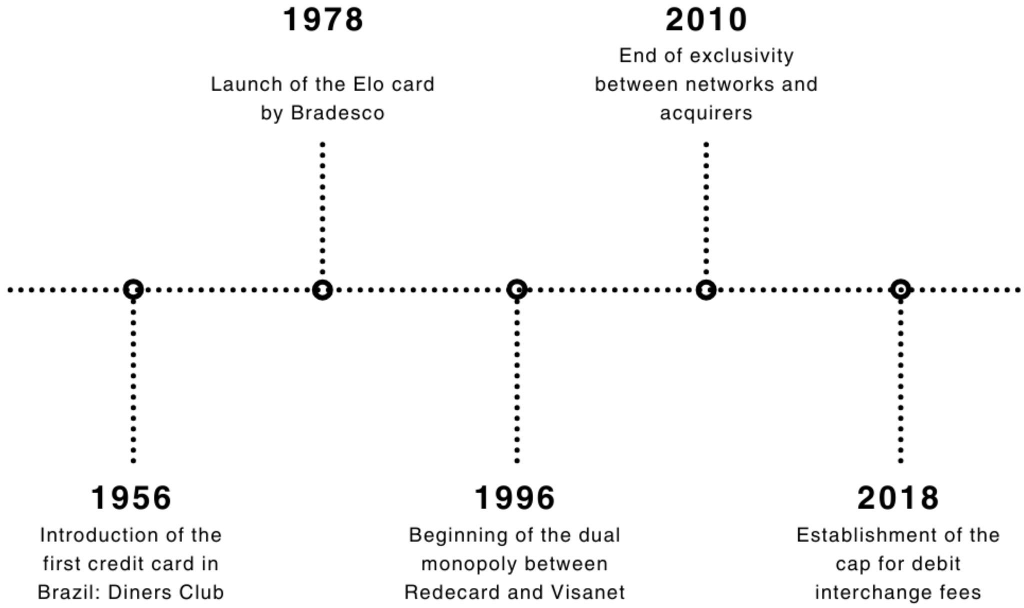

Figure 2.7: Timeline of the Payment Market in Brazil (Source: Developed by the author)

per quarter in each modality grew, over the same period, from R$140.2 billion to R$632.1 billion (an increase of 351%) for credit, and from R$80.49 billion to R$239.1 billion (an increase of 197%) for debit [25].

This data not only demonstrates the structural expansion of card payments in the country but also indicates a faster adoption of credit cards compared to debit cards. This may be associated with the issuers' greater capacity to offer credit, driven by economies of scale, advances in risk analysis models, and the digitalization of the sector. The credit function also offers advantages over debit, such as deferred payment, installment options, and centralized expense management through the billing statement, which may influence user preference.

When analyzing the growth curve in the number of POS terminals from Figure 2.10, we can observe an accelerated adoption of electronic terminals in the country starting from late 2018. This sharp increase in the growth trend may be related to regulations such as Circular No. 3.887, issued on March 26, 2018, by the Central Bank. The reduction in the debit interchange fee (TIC) promoted by this regulation may have encouraged the proliferation of points of sale in the country by allowing acquirers greater margin to price their net MDR, enabling further sector growth through profitability and economies of scale.

In addition, 2018 was marked by two significant IPOs in the payments market that fueled both domestic and foreign investment in Brazil's acquiring sector. In January 2018, PagSeguro went public on the New York Stock Exchange (NYSE), raising 2.7 billion dollars [26]. In the same year, in October, Stone, which had been operating since 2014, also went public in New York, on NASDAQ, raising 1.5 billion dollars [27]. The listing of these companies, which were in the process of consolidating

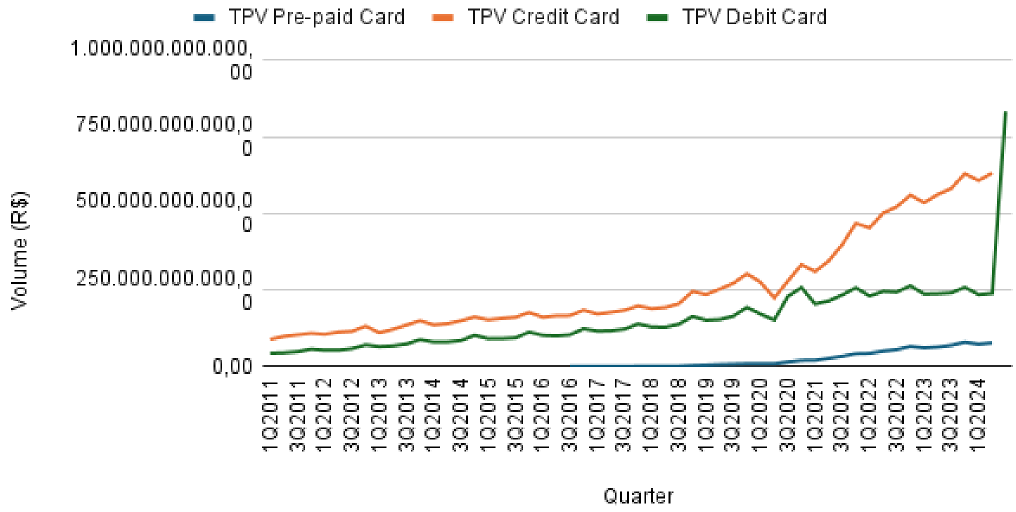

Figure 2.8: Total Value Transacted per Quarter and by Payment Card Type (Source: Developed by the author based on [25])

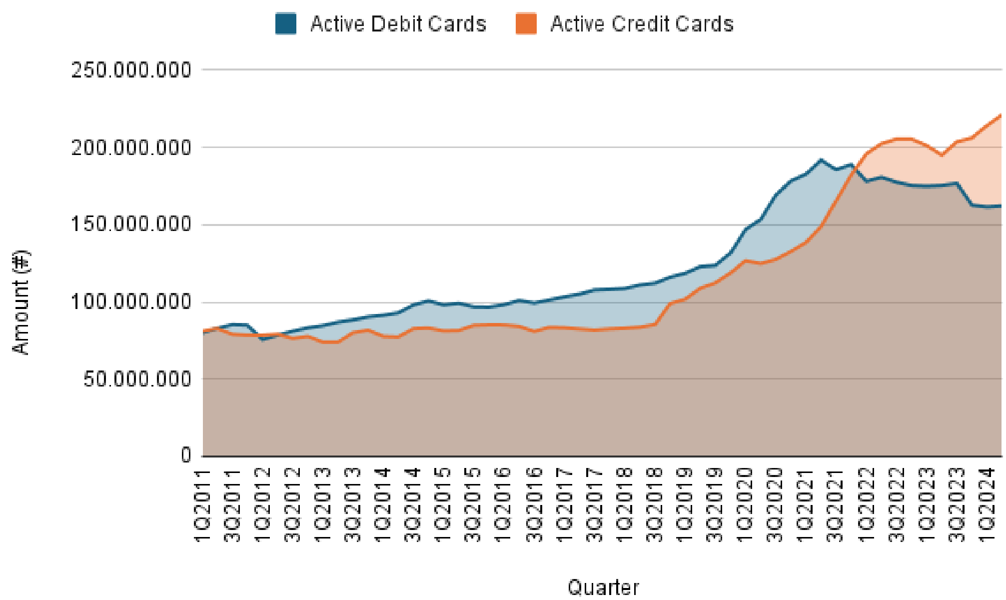

Figure 2.9: Total number of active cards per quarter (Source: Developed by the author based on [25])

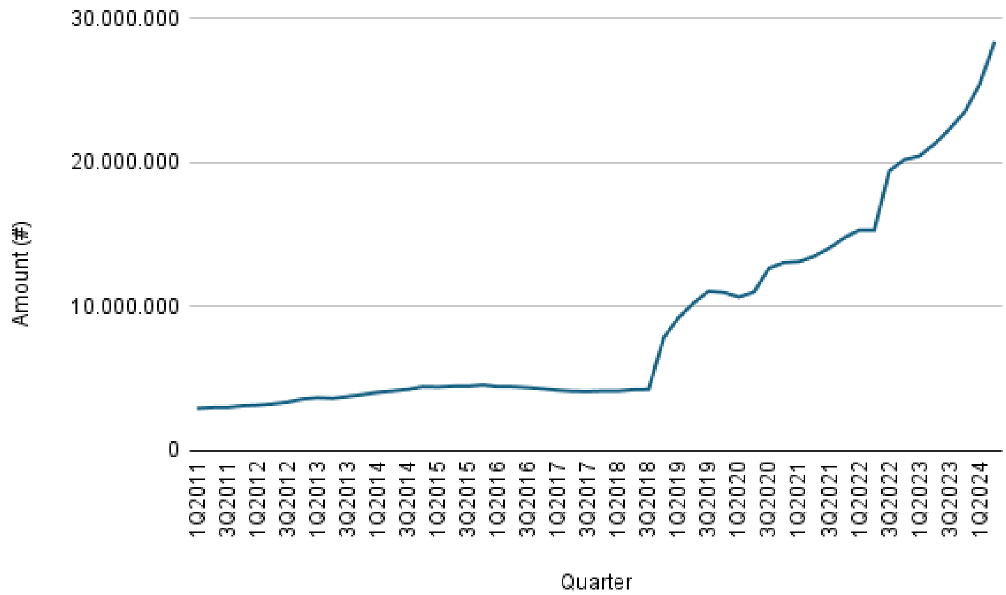

Figure 2.10: Number of active POS per quarter (Source: Developed by the author based on [25])

their position in the market, fostered the inflow of investment into the sector and consequently the popularization of payment acceptance services in the country.

These transformations, combined with the 2010 regulatory milestone that opened the acquiring sector to the entry of new participants, significantly boosted competition in the payments market. As a result, there was a sharp increase in the number of acquirers operating in the country and an intensification in the battle for market share. According to Figure 2.11, companies such as Cielo and Rede, which together held approximately 80% of the market share at the beginning of 2019, began to lose ground to rising acquirers such as Getnet, Stone, PagSeguro, among others, which gradually consolidated their positions in the sector. This demonstrates how competitive rivalry has become increasingly fierce in the industry.

Regarding the evolution of other types of transfers in Brazil, TED transactions and transfers between clients of the same institution stand out as those moving the largest amounts. Combined, they totaled R$16.8 trillion in the second quarter of 2024 [25]. However, considering both volume and number of transactions, the rapid growth of Pix compared to other payment methods is evident, as it can be seen in Figures 2.12 and 2.13. From the fourth quarter of 2020 to the present, Pix has already become the most used payment method in the country (R$6.3 billion in transactions in April 2025), moving more than R$2.6 trillion per month [6].

By observing the historical interchange fees and average discount rates for each function, shown in Figures 2.14 and 2.15, we can see that, despite the downward trend in MDRs across all functions, interchange fees appear to have remained at a steady pattern over time, except for the sharp drop in debit interchange fees in the fourth quarter of 2018 and in prepaid in the second quarter of 2023, related to

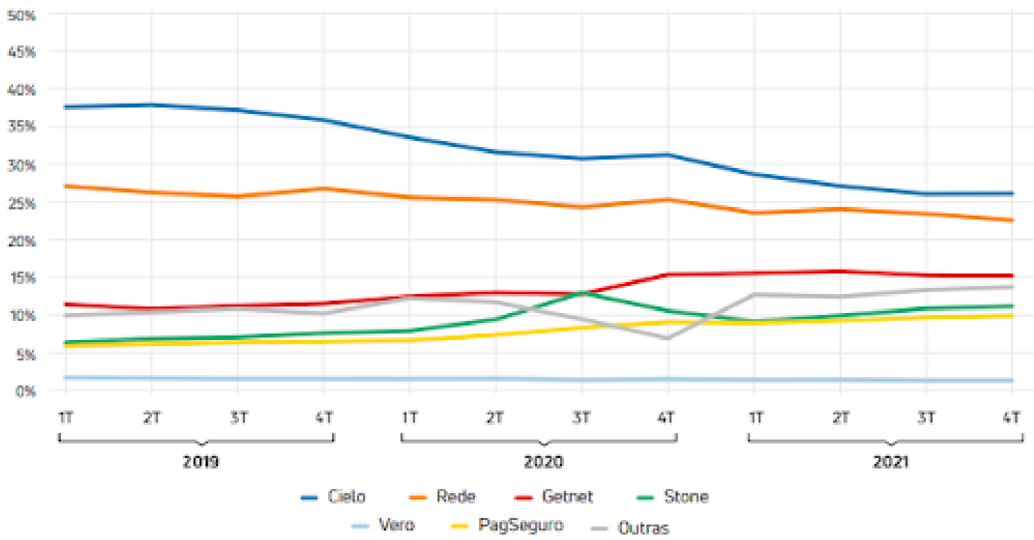

Figure 2.11: Evolution of market share in the acquiring sector (Source: [28])

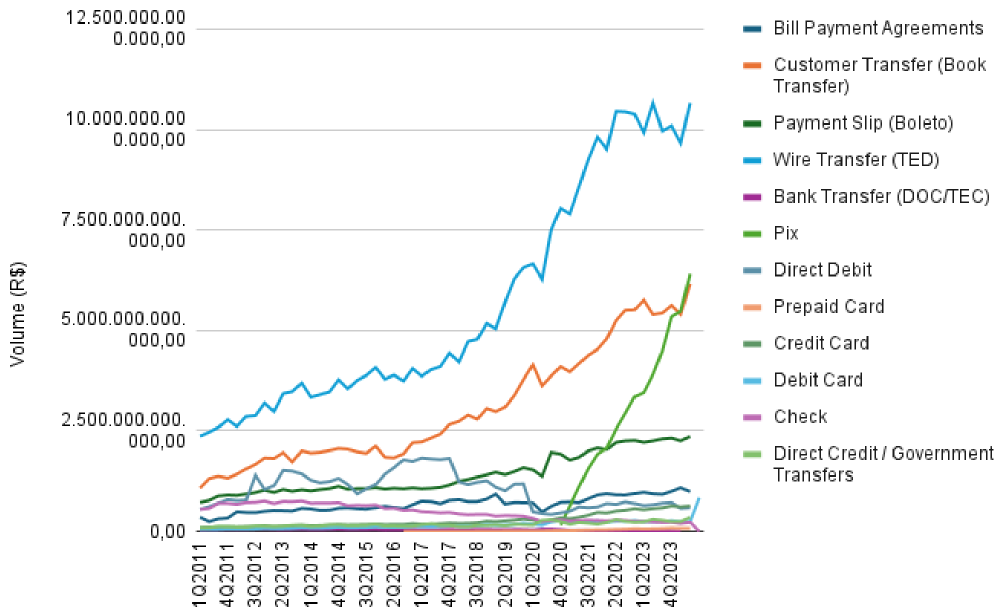

Figure 2.12: TPV by payment method (Source: Developed by the author based on [25])

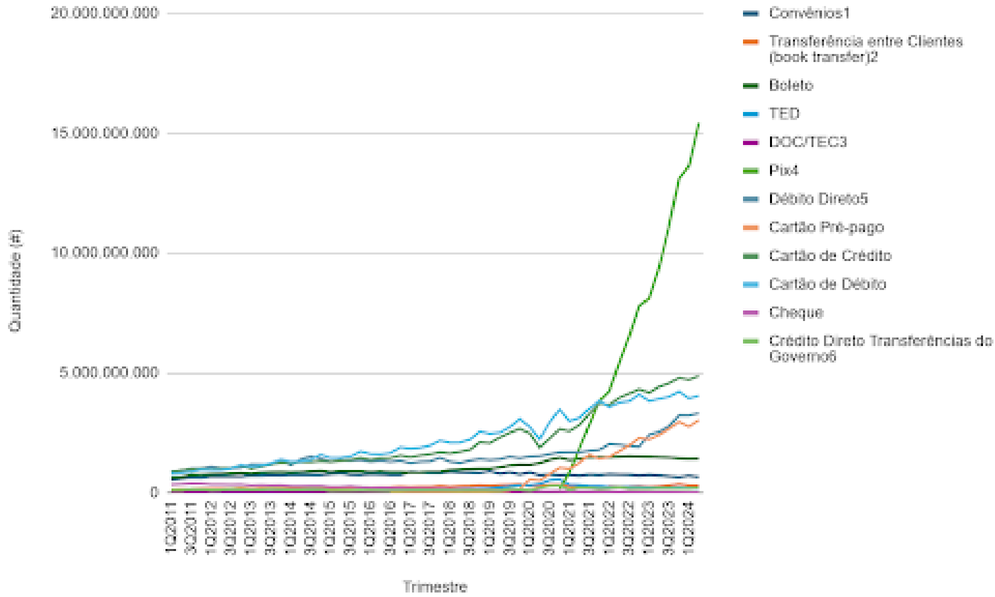

Figure 2.13: Number of transactions by payment method (Source: Developed by the author based on [25])

Central Bank Circular No. 3.887 and Resolution No. 246/2022. Between 2008 and 2016, the ratio between these fees rose from 48% to 62% for credit and from 50% to 55% for debit. The analysis of Figures 2.14, 2.15, and 2.16 allows us to see the evolution of these fees both separately and together, as well as the effects of both regulations on the level of interchange fees applied to debit and prepaid functions.

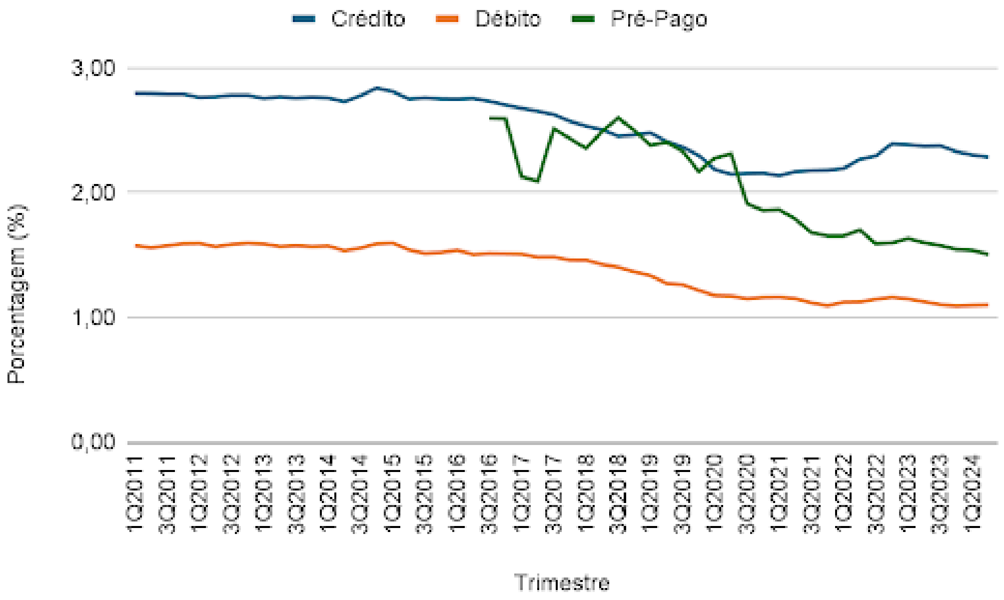

Figure 2.14: Evolution of Merchant Discount Rate per quarter (Source: Developed by the author based on [25])

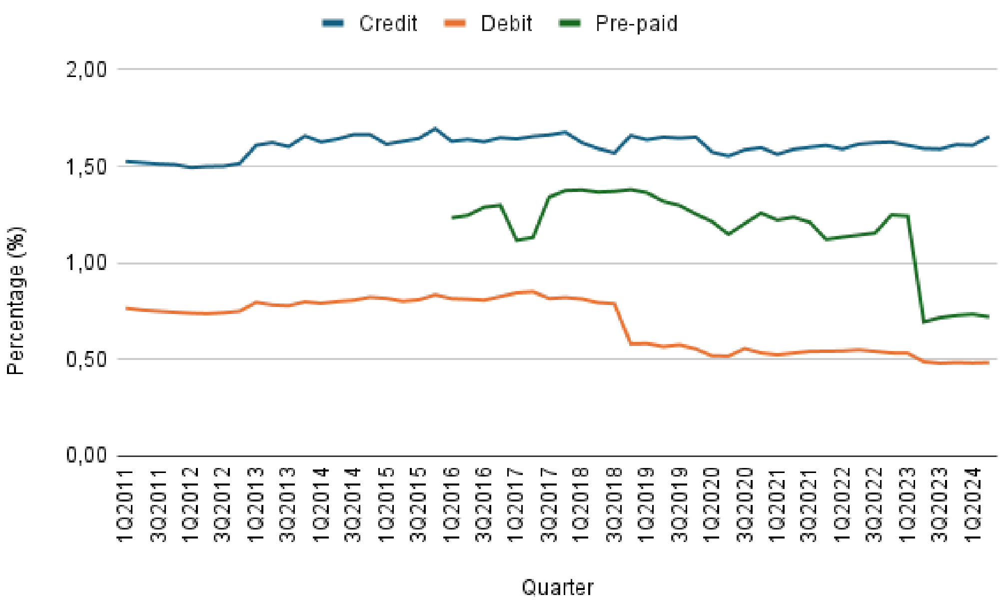

Figure 2.15: Evolution of the interchange fee per quarter (Source: Developed by the author based on [25])

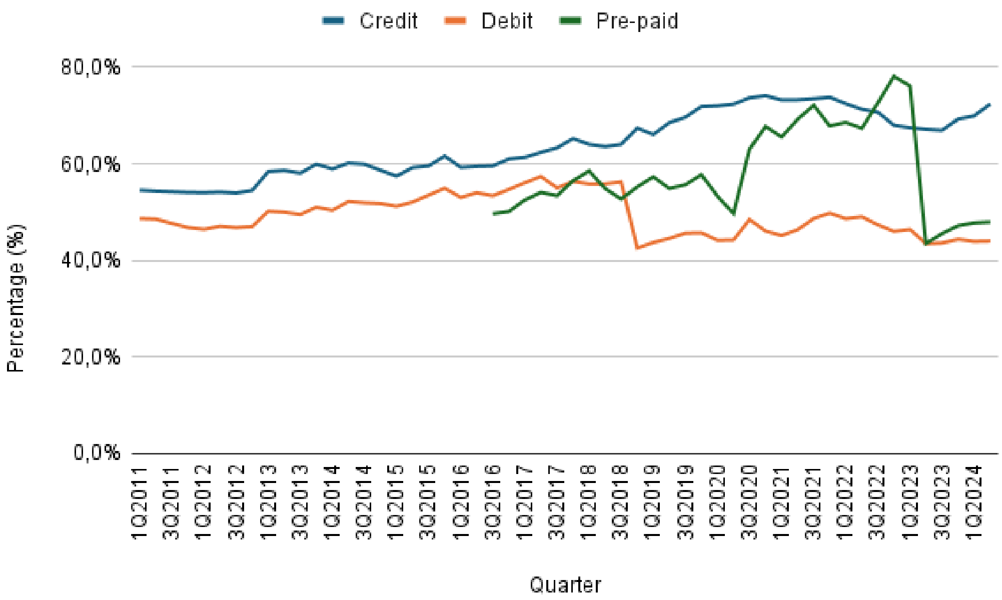

Figure 2.16: Relationship between interchange fee and discount rate per quarter (%) (Source: Developed by the author based on [25])

Chapter 3

Literature Review

To support the analysis carried out in this research, it is necessary to reference the main theoretical and empirical studies that address the operation of the acquiring market and the variables that influence the behavior of the Merchant Discount Rate (MDR). This first chapter presents a literature review on two-sided markets, discussing the composition of the interchange fee (TIC) and its influence on discount rates, as well as other economic and regulatory determinants of MDR behavior. It also reviews recent contributions regarding the influence of Pix on the Brazilian economy and, more specifically, on payment methods. Finally, it presents the Interrupted Time Series (ITS) methodology, used as the basis for the analyses conducted in this study. In doing so, this literature review serves to conceptually ground the hypotheses formulated and the methodological strategies adopted in the present work.

3.1 Two-sided markets

Jean-Charles Rochet and Jean Tirole [29] formalized the concept of a two-sided market. A two-sided market is characterized by platforms that connect two or more groups of end users, allowing interactions between them. In such markets, the utility of a platform increases as more agents join the system on the opposite side (and vice versa). This phenomenon is known as an indirect network externality. In the case of the payment card system, the more buyers use cards, the greater the incentive for merchants to start accepting this payment method. Likewise, the more merchants accept cards, the greater the interest of customers in becoming cardholders. This positive feedback loop generates a critical mass effect and tends to favor concentration in this type of market: platforms with a larger user base tend to attract even more users, strengthening their position relative to competitors [21].

As a two-sided market matures, these network gains tend to decrease marginally, and factors such as congestion may emerge. Congestion occurs when growth on one side of the platform surpasses the capacity of the other side to serve it, thereby compromising the user experience [21]. Nevertheless, network effects remain present and essential to the dynamics of the sector.

A central aspect of Rochet and Tirole's theory [30] is that, in two-sided markets, the price structure matters more than the price level itself. Platforms tend to subsidize one side of the market and charge the other, based on each group's willingness to pay. As a result, it is common for one side to pay little or nothing for the service, while the other bears most of the costs. In the payment card market, cardholders are often exempt from any fees and may even receive benefits and rewards for using the card (such as mileage programs, points, cashback, etc.), while merchants pay discount rates on each transaction processed. This configuration allows the network to internalize the network externalities: since merchants are less price-sensitive (less elastic demand) than cardholders, the card network tends to charge them more relative to buyers, thereby encouraging more cardholder adoption and increasing the platform's value [30].

In this way, the interchange fee (TIC) functions as a balancing mechanism between the two sides of the market, transferring revenue between buyers and sellers. The 2010 "Report on the Payment Card Industry" by the Central Bank highlights the importance of the interchange fee in attracting users to the card payment system. Without an appropriate fee, issuers would have little incentive to subsidize card issuance, reducing the platform's value. Therefore, defining the optimal price structure (annual fees, discounts, rates) is crucial to the platform's success [30].

3.2 Determinants of the Interchange Fee

There are several factors that can influence the interchange fee (TIC). The literature on the subject mainly identifies the following determinants:

Competition between card networks: The level of competition between card networks can affect the pricing of the interchange fee. According to Perez and Bruschi [2], however, this effect is not always predictable. Increased competition in the sector may reduce fees for cardholders but it can raise the prices charged to merchants through discount rates, due to network effects.

In the case of a card network monopoly, the owner of the payment scheme may set the interchange fee to issuers in a way that maximizes its profits [29]. In a scenario of competition between platforms (such as Visa and Mastercard), there may actually be upward pressure on the interchange fee. Higher interchange fees attract more issuers, so networks are pushed to set higher prices to bring more banks and financial institutions into their payment scheme, thereby increasing the number of cards and transactions processed [29].

Competition between issuers: The interchange fee is also determined by negotiations and power dynamics among issuers. When a few banks control the largest share of the card market, they have the leverage to push interchange fees higher with the networks, increasing their revenues from card issuance [31]. Rochet and Tirole [32] highlight that, in schemes where issuers held significant market power, the equilibrium interchange fee could end up above optimal levels, favoring issuers at the expense of acquirers and merchants.

Network externalities and willingness to pay: As explained earlier, the two-sided platform models formalized by Rochet and Tirole [29] indicate that network externalities and the willingness to pay of each side are key factors in determining the optimal interchange fee. If the utility for merchants in accepting card payments (increased sales opportunities, customer convenience, etc.) is greater than the utility for cardholders in using cards instead of other payment methods, merchants will become less sensitive to increases in card acceptance costs (less elastic demand). In this case, the payment scheme operator can shift service costs between the two sides of the platform by increasing the interchange fee, which impacts the merchant discount rate (MDR) paid by businesses [2].

On the other hand, setting excessively high interchange fees may discourage merchants from accepting card payments, particularly if such acceptance does not bring significant benefits to cardholders [2]. This would also reduce the value of the payment method for cardholders, potentially undermining the sustainability of the entire system.

Interest rates: Rising interest rates in the economy are strongly tied to transactions made with credit cards. Higher interest rates directly affect the issuer risk and funding costs, as they act as creditors to card users, and can impact interchange fee pricing in two ways. In a context where the benefits to cardholders are not affected (low risk of default), these costs can be passed on to acquirers and merchants through higher interchange fees. On the other hand, higher interest rates in the economy are usually accompanied by increases in revolving and installment credit rates, which raise the perceived risk for cardholders and reduce the attractiveness of using the card. As a result, merchants may internalize this loss of platform utility, becoming less willing to bear high acceptance costs [2].

Institutional rules and regulation: The regulatory environment and the operating rules of payment schemes also influence interchange fees. Contractual restrictions imposed by networks such as the honor all cards rule (which requires merchants to accept all cards from a network, without the option to refuse) and the no-surcharge rule (which prevents merchants from charging different prices for card payments) reduce merchants' bargaining power against increases in discount rates [32].

When regulators act to prohibit or mitigate the effects of such rules, merchants gain more freedom to respond to increases in interchange fees, passing these costs on to customers via surcharges or by refusing certain cards. This, in turn, pressures card networks to adjust their interchange fees in order to maintain transaction volumes.

In addition, regulators can directly intervene in interchange fee pricing to combat antitrust practices or foster competition in the sector, typically by setting caps on this fee. Several countries have already imposed such caps. In 2015, the European Union established a cap of 0.3% for credit card interchange fees and 0.2% for debit cards [33]. In 2003, the Reserve Bank of Australia set a maximum average value of 0.5% for credit card transactions and removed restrictions such as the no-surcharge rule, later establishing limits for debit card charges as well [34].

In Brazil, Central Bank Resolution No. 246/2022 set a maximum average rate of 0.5% for debit transactions (0.8% per transaction) and 0.7% per transaction for prepaid cards [24]. In addition, Law No. 13.455 of 2017 allowed merchants to charge different prices depending on the payment method, granting them greater bargaining power [2].

3.3 The Relationship Between TIC and MDR

The interchange fee and the merchant discount rate (MDR) are closely connected, since the former is a significant component of the latter. When the card network changes the value of the interchange fee, this adjustment impacts the costs borne by the acquirer to settle transactions, thereby affecting the MDR charged. In competitive acquiring markets, it can be assumed that acquirers tend to pass on the cost of interchange fee variations to merchants, at least partially. In this way, increases in the interchange fee tend to raise the merchant discount rate, while reductions in the interchange fee create room for decreases in the MDR charged. However, this depends on there being sufficient competitive pressure to force acquirers to pass on such changes [30] [15].

However, this depends on there being sufficient competitive pressure to force acquirers to pass on such changes [30] [15]. If acquirers hold substantial market power, a reduction in the interchange fee may not be immediately transferred to merchants, instead being absorbed as additional profit. On the other hand, when competition among acquirers is stronger, the MDR tends to reflect more directly the costs associated with the interchange fee [30]. It is even possible that, in an environment of increasing competition, acquirers may absorb rising interchange costs by reducing their net MDR in order to maintain their market position [15].

3.4 Interrupted Time Series - ITS

The Interrupted Time Series (ITS) analysis is one of the most robust quasi-experimental statistical models, being appropriate for evaluating the impact of an intervention (public policy, regulation, or macroeconomic event) on a variable observed over time, by comparing the trend of the series before and after the intervention. This method is particularly useful in contexts where randomized clinical trials are not feasible, as is the case in this study, given that we do not have a symmetrical control group unaffected by the adoption of Pix with which to compare the results [35] [36].

In the standard ITS model discussed by Linden [35] and based on the studies of Huitema and McKean [37] [38] and Simonton [39] [40], when only one group is present for analysis, this comparison is carried out through linear regressions on time variables, as illustrated below:

$$Y(t) = \beta_0 + \beta_1 \cdot T(t) + \beta_2 \cdot X(t) + \beta_3 \cdot (X(t) \cdot T(t)) + \varepsilon(t) \tag{3.1}$$

Where Y(t) is the value of the dependent variable in a given period; $\beta 0$, the

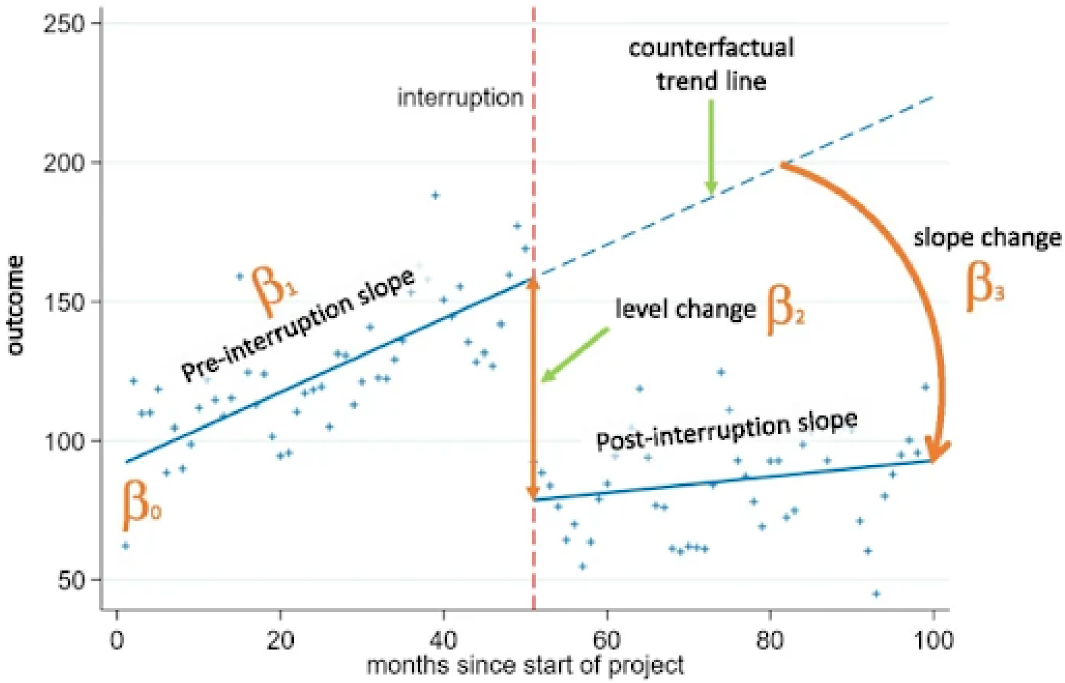

Figure 3.1: Basic structure of an ITS with intervention (Source: [41])

intercept (initial level); $\beta 1$, the slope of the series over time, represented by T; $\beta 2$, the level change after the intervention, represented by the boolean X; $\beta 3$, the slope of the series in the period after the intervention, represented by XT. $\varepsilon(\mathrm{t})$ corresponds to the residual of each period t. A graphical example of the relationship between these coefficients can be seen in Figure 3.1.

Regarding the behavior of the variables, T starts the first period of the experiment with a value of 1 and increases by one unit until the last period. X takes the value 0 for all periods prior to the intervention and 1 for all periods thereafter, in order to capture level changes that may be observed immediately after the intervention. Consequently, XT has the same value as T during the post-intervention period but is null in all preceding periods.

The robustness of Interrupted Time Series (ITS) analysis lies in its ability to control for prior trends, capture structural changes in time series, and minimize selection bias even in the absence of a control group. Unlike simple pre- and post-comparisons, ITS incorporates the secular trend as a counterfactual baseline, allowing one to distinguish between natural fluctuations and actual intervention effects [36] [35]. The model has already been successfully applied in studies of tobacco control tax policies [35], structural reforms in health systems [42], and regulatory changes for pharmaceuticals [43]. These applications demonstrate the versatility of ITS in analyzing real-world events.

However, as Lopez Bernal et al. [36] point out in their work “A Methodological Framework for Model Selection in Interrupted Time Series Studies”, the choice of the impact model in ITS studies is crucial for correctly estimating the effect of an intervention. The impact of an intervention on a time series may be, for example,

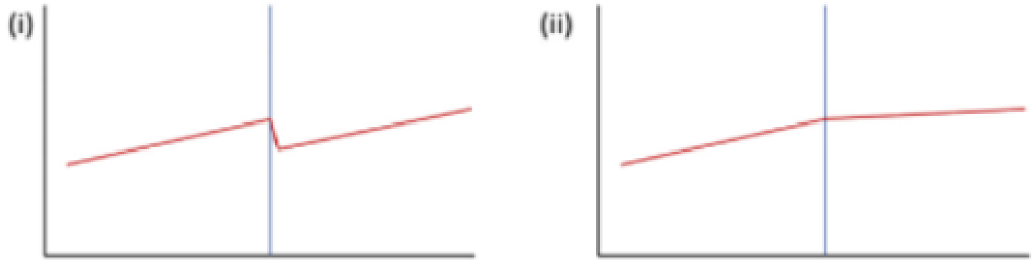

Figure 3.2: Illustrative example of impact models for interventions with abrupt effects (left) and gradual effects (right) (Source: [36])

abrupt or gradual. One-time events or immediate regulatory measures (such as the imposition of caps or budget cuts) generally generate abrupt effects, which are observed as a sudden change in the level of the series, but not necessarily accompanied by a change in slope. An illustrative example of abrupt effects can be seen in Figure 3.2. More complex interventions, with gradual adoption or adaptation by individuals in the treatment group, may generate changes in the slope of the series without necessarily affecting its level. An illustrative example of gradual effects in the time series can also be seen in Figure 3.2.

In addition, some interventions may have an immediate effect or present some type of lag. This depends on the time it takes for the series to absorb the impacts of the intervention. For example, a public health campaign may alter the behavior of institutions immediately, but its effects on clinical outcomes, such as hospitalizations or mortality, may take months to appear. The authors also draw attention to effects that diminish over time. In other words, when the initial impact of the intervention progressively loses strength. In such cases, it is necessary to use specific terms to capture this effect.

Lopez Bernal et al. [36] warn about the risks of adopting overly flexible models or models based solely on the best statistical fit to the data, as this may generate false positives. They recommend that researchers define the form of the impact in advance, based on theoretical hypotheses and knowledge of the intervention under study, avoiding decisions guided only by empirical criteria. The choice between different types of impact should consider the speed of implementation of the intervention, the nature of the impact, and possible limitations such as ceiling or floor effects.

3.5 The Effects of Pix in The Acquiring Market

Pix is an instant payment system launched by the Central Bank of Brazil with the objective of addressing gaps in the national payment system, promoting greater inclusion, competition, and efficiency. Pix enables real-time transactions, available 24/7, for any individual or business with a bank account [4]. Pix was rapidly adopted following its introduction. Within little more than a year, Pix had already surpassed wire transfers (TED and DOC) in number of transactions. In the first quarter of 2022, with 4.3 billion transactions processed, Pix became the most widely used electronic payment instrument in the country, surpassing even the number of credit and debit card transactions [8]. By December 2023, 149 million individuals and 15 million companies were already using Pix [9].

For traditional merchants, Pix quickly stood out as a low-cost alternative to cards. In Q4 2022, the average cost of accepting Pix was 0.33%, compared with 1.13% for debit cards and 2.34% for credit cards [4]. This means that, in addition to offering instant settlement of funds (unlike credit card transactions, for example), Pix also had the potential to avoid costs associated with high merchant discount rates or fees related to the provision of POS terminals. These cost savings have led merchants to encourage payments via Pix, including the possibility of passing on cost differences or offering discounts to consumers, particularly after Law 13.455/2017, which allowed merchants to charge different prices for different payment methods [2].

For consumers, Pix represents a fast and free payment method (for individuals), reducing the need to carry and handle cash or cards. Buyers can simply scan a QR code with their phone camera to make transfers. This convenience made Pix one of the preferred payment methods among Brazilians for purchasing goods and services. In 2023, Pix recorded around 42 billion payments, a 74% increase compared with the previous year, surpassing by approximately 23% the combined number of credit and debit card transactions [44]. In e-commerce, the share of Pix transactions rose from 22% to roughly one-third of all transactions between 2021 and December 2023, while card transactions fell by 2% over the same period [44]. These data reveal a behavioral shift among users, who increasingly adopt Pix due to its speed and simplicity.

From the perspective of financial institutions, the effects of Pix are significant and require adaptations to the business model. Card issuers face risks of reduced interchange revenue as more consumers choose Pix over cards [44]. Pix also eliminated (for individuals) or reduced (for businesses) fees that were previously charged for interbank transfers such as TED and DOC, further eroding banks' traditional revenue streams. On the other hand, recent studies suggest that Pix fosters greater inclusion in the banking system, potentially expanding long-term business opportunities for banks. Sampaio and Ornelas [9], in a BIS study, found that the introduction of Pix in Brazil led to an increase in the number of active bank accounts, greater use of banking services, and even expanded access to credit. Thus, while issuing banks lose part of their traditional fee revenues, Pix has contributed to broadening the base of banked customers and may stimulate the development of new financial products.

For acquirers, Pix poses a direct competitive challenge. The low cost of Pix and the reduction of intermediaries between transactions threaten the main source of revenue for acquirers, which is the MDR. Although fees are often charged for accepting Pix via POS terminals, these are generally lower than the MDR on credit and debit card transactions. Moreover, merchants do not need POS devices to accept Pix, since a QR code can be generated independently, making POS terminals more of a convenience tool than a necessity. Beyond MDR, other services offered by acquirers are also at risk. Goldman Sachs warned its clients that the growth of Pix could limit the use of credit cards and the volume of receivables prepayment, a crucial revenue stream for acquirers [44]. A significant portion of acquirers' revenues comes from charging merchants to anticipate their receivables from credit sales (normally paid within 30 days). If more credit transactions migrate to Pix, demand for receivables prepayment declines, further impacting acquirer revenues.

In light of this scenario, major acquirers in Brazil have revised their strategies. In 2022, for example, Getnet (part of the Santander Group) delisted its shares from the stock exchange. In the following year, Cielo, the market leader in acquiring services, announced plans to go private, as part of a restructuring strategy to offer a broader portfolio of integrated products and reduce its dependence on traditional card fees. According to Brazil's Central Bank, one of Cielo's controlling shareholders, this decision was driven by "transformations" and increasing competition in the payments sector [44]. These developments illustrate how acquiring companies are reassessing their market positioning, integrating more technology into their platforms, and focusing on value-added services to remain competitive.

In 2022, the then-president of the Central Bank of Brazil even stated that "credit cards will cease to exist at some point" in light of the transformations brought by Pix and Open Banking [44]. While this may be an extreme prediction, it underscores expectations of profound changes in the payments market.

In that same year, financial institutions began offering "Guaranteed Pix" or "Credit Pix", allowing customers to split or defer Pix transfers using their credit card or account limits. Nubank, the largest digital bank in Brazil, ended 2023 with 13.6 million customers using Pix via credit card, representing a 166% increase compared with the previous year [44]. This example illustrates how card issuers and fintechs are reinventing their product portfolios by integrating Pix into their financial solutions to retain customers.

In conclusion, the implementation of Pix in Brazil triggered profound changes in the country's financial structure, reshaping costs and revenues for the involved agents and altering consumer behavior. The literature and available data indicate that Pix has become a milestone in the modernization of the payment system, promoting greater integration, competition, and reduced reliance on physical payment instruments. The tool also continues to evolve: new functionalities, such as scheduled Pix payments and Pix with credit, are being periodically launched and integrated into the financial ecosystem. Thus, Pix not only coexists with other instruments but redefines their roles and market share, largely fulfilling the purpose outlined by the Central Bank: to make payments faster, cheaper, safer, and more accessible.

3.6 The Regulatory Impact of the Caps on Debit TIC

Circular No. 3.887/2018, issued by the Central Bank of Brazil on March 26, 2018, established caps for interchange fees (TIC) in domestic debit card transactions. The regulation, which came into force on October 1, 2018, set the maximum weighted quarterly average TIC at 0.5% and the maximum per individual transaction at 0.8%. The main objectives of these caps were to encourage the use of debit cards, increase transparency in the pricing structure of payment instruments, reduce cross-subsidization between instruments, and combat the overuse of more expensive instruments such as credit. In other words, it was expected that the reduction in debit TIC would result in a lower Merchant Discount Rate charged to merchants, which would then be passed on to consumers through lower prices for debit purchases. This pass-through would make debit relatively less costly than credit, thereby inducing migration between payment methods. The measure is part of a broader effort to improve the Brazilian Payment System, based on the economic literature that suggests TIC tend to be excessively high in two-sided markets [45] [46] [47]. Thus, the establishment of caps would act to increase social welfare by correcting price arbitrages between issuers, acquirers, merchants, and cardholders. Interchange fee caps were already in place in other jurisdictions, most notably in the European Union since 2015, with efficiency and end-user cost reduction objectives similar to those pursued in Brazil. In this context, Circular No. 3.887/2018 was the first regulation to directly intervene in debit interchange fees in Brazil, complementing previous competitive measures in the card market [48].

The consequences of adopting Circular No. 3.887/2018 were analyzed by the Central Bank in Special Study No. 106/2021. The econometric analysis examined acquiring and issuing data before and after the cap to assess its effects on issuer revenues, acquirer costs (MDR), transaction volume, and other scheme fees. As expected, the regulatory cap significantly reduced debit interchange revenues for issuers. More specifically, there was a 32.4% reduction in average revenue per active debit card derived from interchange after the cap (comparing Q4 2018 to Q1 2020). This revenue reduction corresponded to about 91.5% of the effective reduction in the average interchange fee during the period, implying that the natural growth trend in transaction volume (greater card usage and higher-value transactions) partially offset the percentage reduction imposed on TIC. In other words, although the average interchange fee fell to the regulated cap level (0.5% on average), continuous growth in debit card use during the period softened the impact on per-card revenue. However, no evidence was found that issuers offset this revenue loss by raising credit card interchange fees. Credit card interchange revenues remained virtually unchanged, with no statistically significant increase following the measure.

From the perspective of merchants and acquirers, the reduction in debit TIC was reflected in a gradual reduction in the MDR charged to merchants for debit transactions. The study confirmed partial but increasing pass-through of the lower interchange costs to the retail sector. In the period immediately after the cap took effect (Q4 2018), only about 16.9% of the TIC reduction had been passed on to merchant MDRs. This pass-through rate grew steadily in subsequent quarters, reaching around 64.3% by Q1 2020. In concrete terms, although acquirers initially retained most of the benefit of lower interchange (possibly to rebuild margins or due to contractual lags), competitive pressure throughout 2019 gradually transferred these cost reductions to merchants. This finding is significant, as it confirms a substantial decrease in average debit MDR after the regulation, even if the pass-through was neither immediate nor complete. Furthermore, the reduction in debit MDR undoubtedly narrowed the cost gap between debit and credit: prior to the cap, debit discount rates were higher and closer to those of credit, but after the cap the expectation (partially confirmed by the >60% pass-through) was that debit would become a relatively less costly payment method for merchants and, potentially, for consumers, provided that savings were passed on to final prices.

One of the main objectives of the measure was to change incentives in payment method usage, encouraging greater use of debit cards instead of more expensive instruments such as traditional credit cards, especially when used as substitutes for debit. In the period analyzed, up to early 2020, no statistically significant increase in debit card usage was observed that could be attributed to the cap, compared to the previous trend. In other words, the measure did not increase debit's share among payment methods in the first 18 months, contrary to initial expectations. On the other hand, it is noteworthy that there was no decline in debit usage either, which could have occurred had issuers sought to offset revenue losses by discouraging debit usage (for example, by charging cardholder fees or reducing their benefits). The relative stability in debit card usage therefore suggests that the cap had no perceptible adverse effects on debit's acceptance or attractiveness for consumers and merchants. However, the expected benefits in terms of increased debit usage had not yet materialized in the short-term horizon analyzed. It is important to emphasize that effects on transaction volumes may take longer to consolidate, and price differentiation between debit and credit may produce behavioral responses only gradually.

Finally, the study examined possible adjustments in other scheme fees resulting from the new regulation, particularly those charged by Visa, Mastercard, and others. In theory, there was concern that scheme owners might react to the TIC cap by changing their own fees (for example, raising scheme fees charged to acquirers, thus increasing their costs, or reducing scheme fees paid to issuers, thereby compensating them in other ways). However, no evidence was found that the reduction in debit TIC triggered such adjustments in scheme fees. Throughout the period examined, scheme fees paid by participants remained stable, suggesting that card networks did not need to alter their fee structures in direct response to the TIC cap. This outcome supports the conclusion that the regulation was able to achieve its main target (interchange remuneration between issuers and acquirers) without causing significant spillover effects in other parts of the card market.

3.7 The Effects of The Pandemic on The Acquiring Market

The Covid-19 pandemic was officially declared by the World Health Organization on March 11, 2020, a few days after confirmation of the first case of the disease in Brazil on February 26 of that year [49]. Its most intense effects lasted until early

2022, when the then Minister of Health, Marcelo Queiroga, declared the end of the public health emergency in the country on April 22 [50].

This period was marked by one of the most severe economic contractions in Brazil's recent history. In 2020, Gross Domestic Product (GDP) declined by 4.1% compared to the previous year, closing with a sharp drop especially in the services sector (-4.5%). This general contraction was the largest in decades and was associated with a deterioration in labor market conditions and household income. On the demand side, household consumption expenditure fell by 5.5% in 2020, the steepest annual drop since 1996, reflecting worsening employment conditions and social distancing measures imposed during the pandemic. Sectors dependent on the movement of people were the hardest hit: for example, family-related services (such as bars, restaurants, and hotels) and transportation experienced the largest contractions, underscoring the severe effect of social isolation on traditional in-person consumption [51].

To mitigate these effects, the federal government launched in April 2020 the "Auxílio Emergencial" (Emergency Aid), the largest income transfer program in the country's history, which benefited around 68 million Brazilians throughout the year, totaling approximately R$ 293 billion in expenditures [52]. This massive income injection played a crucial role in sustaining consumption, especially among poorer households. Analyses by the Central Bank of Brazil indicate that lower-income groups experienced proportionally smaller declines in consumption and recovered more quickly, likely as a result of the emergency transfers. In contrast, higher-income households reduced their spending more sharply during the worst moments of the crisis [53]. In other words, the emergency cash transfers acted as a safety net for the most economically vulnerable groups, cushioning the contraction in basic consumption and partially absorbing the economic shock.

Isolation measures and fear of contagion radically reshaped the consumption habits of the Brazilian population. With most physical stores, leisure facilities, and educational institutions closed or operating under restrictions, consumers turned to e-commerce, delivery, and other digital alternatives. The result was an unprecedented acceleration of digital consumption. According to industry estimates, e-commerce revenues more than doubled in 2020 (January to November) compared to the previous year, reaching R$ 115 billion [54]. At the same time, remote purchases with credit or debit cards increased 32.2% in 2020, totaling R$ 435.6 billion, a growth directly driven by social isolation, which increasingly pushed people and businesses toward online retail. In Q4 2020, this phenomenon peaked: one out of every three credit card purchases was remote (online or via app), demonstrating the consolidation of new habits of distance consumption [55].

In parallel, there was a growing preference for payment methods involving less physical contact, aimed at reducing sanitary risks. This strongly boosted the adoption of contactless payments. In 2020, the value of contactless transactions reached R$ 41 billion, a 469.6% increase compared to 2019. This surge was facilitated by sector initiatives, such as raising the limits for no-PIN transactions (from R$ 50 to R$ 100 in mid-2020, and later to R$ 200 at the end of the year) [55]. As a result, many consumers adopted contactless cards and digital wallets in their daily lives, reducing the use of cash. Industry estimates suggest that between 20% and 30% of purchases that migrated from physical to digital channels during the pandemic are expected to remain in e-commerce even after the end of the health crisis [56].

Within this context, the Brazilian payments system underwent accelerated transformations. Trends that had already been unfolding over the past decade intensified. There was a rapid replacement of physical means (cash, checks) by electronic and digital methods, driven by the adoption of new financial technologies. Notable developments included the expanded use of contactless cards, the growth of online card transactions, the mass adoption of Pix, and the increased use of digital accounts offered by fintechs [28]. Even amid recession, electronic payments gained ground: in 2020, transaction volume with credit, debit, and prepaid cards reached R$ 2 trillion (a real increase of 8.2% over 2019) [55]. This expansion raised the share of digital payments in both household spending and GDP: by the end of 2020, cards accounted for about 46% of household consumption (up from 40% before the crisis) and 30.9% of GDP (compared to 28% in 2019) [55].

The composition of payments also changed during the pandemic. While credit cards (traditionally used for installment purchases and higher-value items) grew modestly in 2020 (+2.6%, reaching R$ 1.18 trillion), debit cards (associated with day-to-day spending) rose 14.8%, totaling R$ 762 billion in transactions. Even more striking was the growth of prepaid cards, whose usage more than doubled (+107%), reaching R$ 45.3 billion in 2020. In terms of volume, Brazilians conducted 23.3 billion card transactions in 2020 (a 3.6% increase in the number of operations compared to 2019) [55]. In summary, even amid economic contraction, the use of electronic payment methods grew both in value and in volume, reflecting the resilience and adaptability of the payments market to new demands of safety and distancing.

In the acquiring sector, the effects of the pandemic also accelerated competitive dynamics. In previous years, increasing competition ("the POS War") had already been observed, with new entrants (fintechs and independent acquirers) gaining ground from traditional players. This trend deepened between 2020 and 2021. Industry data show that large acquirers such as Cielo and Rede lost market share to newer firms such as Stone, PagSeguro, Getnet, and others. In Q1 2021, for the first time, Cielo's market share fell below 30%, illustrating the redistribution of shares among competitors [28]. The increase in competition tends to benefit merchants by reducing discount rates charged for payment acceptance services. Thus, the acquiring market became more competitive with acquirers pressured to innovate and cut costs in order to keep pace with the digital transformation of retail.

3.8 The Influence of Interest Rate on TIC and MDR

When a bank or financial institution issues a credit card to its client, the issuer assumes the role of creditor, bearing the risks and costs of credit linked to the payment of the bill within the agreed period. In this context, it is important to highlight that, in the case of credit cards, the interchange fee (TIC) helps issuers cover the costs of the interest-free credit period and provide benefits to users [57]. Thus, the basic interest rate of the economy may influence the level of TIC considered optimal: higher interest rates increase the opportunity cost of the resources involved in transactions, creating pressure for higher TICs to compensate issuers, while lower interest rates reduce this need for additional remuneration.

In summary, the Selic (Brazilian policy interest rate) affects the system's equilibrium: when elevated, it increases the financial value of the postponed cash flow inherent to credit card transactions (the grace period), raising the relevance of the TIC for issuers; when reduced, it decreases the weight of this financial component, potentially opening room for cuts in interchange fees and in the merchant discount rate (MDR), provided that there is sufficient competition in the acquiring market to pass on these reductions to merchants.

In the case of Brazil, the expansion of electronic means of payment and the entry of acquiring fintechs helped ensure that reductions in TIC, as well as the effects of lower policy interest rates, were effectively passed on to commerce. As shown in Figure 3.3, between 2017 and 2020, a period marked by the Selic falling to historical lows (reaching 2% per year in 2020), average MDR rates either remained stable or declined, reflecting the low cost of capital and the competitive environment.

From 2021 onwards, however, the reversal of the monetary cycle highlighted the direct impact of the Selic on MDR price formation. With the aggressive rise in the policy rate (from 2.0% per year at the beginning of 2021 to 13.75% per year in 2022), there was strong cost pressure on acquiring companies and a generalized movement of fee adjustments in the card sector [58]. A survey conducted by investment bank UBS BB revealed that, after six consecutive years of decline, the average discount rate rose significantly again in 2022: MDR charged on credit transactions increased from 2.1% (October 2021) to 2.8% (September 2022), while on debit transactions it rose from 1.3% to 1.6% in the same period [58]. According to the analysis, this inflection was driven "mainly by higher funding costs, highlighting the increase in the basic interest rate (Selic) during the period" [58].

In other words, the increase in funding and working capital costs, directly linked to the increase in the Selic rate, led acquirers to raise the fees charged to merchants, partially reversing the efficiencies gained during the previous years of low interest rates. This effect confirms the sensitivity of the merchant discount rate (MDR) to monetary conditions: higher interest rates increase the cost of holding receivables until settlement, creating pressure either to compress margins or to pass on these costs to merchants.

In the Brazilian context, where credit card sales are traditionally settled with merchants in approximately 30 days (a period that, in practice, represents consumer financing at no apparent cost), a high Selic rate substantially increases the opportunity cost of this 30-day window. Many merchants choose to advance their card receivables (through financial discounting) to mitigate the impact on cash flow. However, this

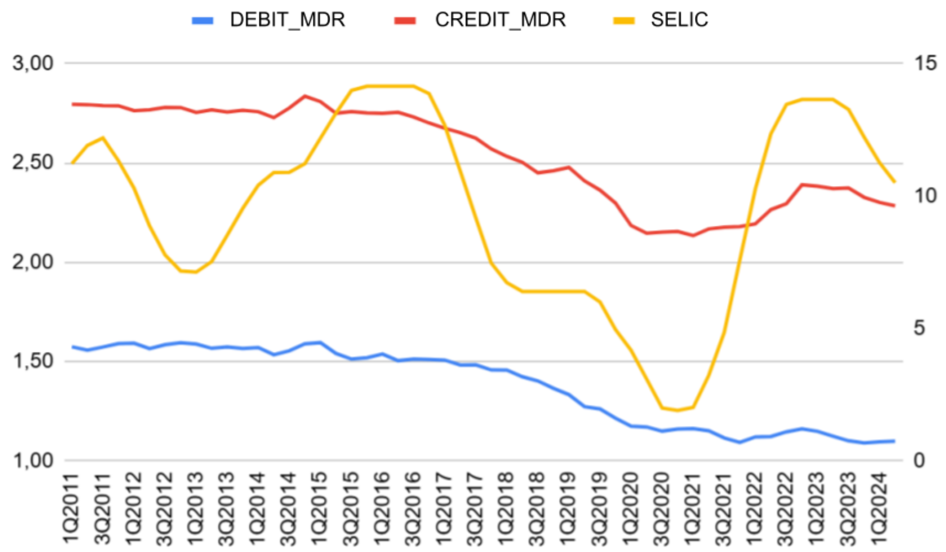

Figure 3.3: Evolution of MDR and Selic rates over time (Source: Developed by the author based on [25][59])

discount becomes more burdensome when the policy rate rises. Indeed, the same UBS BB survey reported an increase in the share of merchants resorting to receivables anticipation (from 45% in 2021 to 59% in 2022), reflecting the greater need for working capital in a more restrictive financial environment [58]. Thus, the rise in interest rates increased both the direct cost of the MDR and the demand for associated financial services (anticipation), amplifying merchants' overall financial expenditures.

The challenge faced by payment scheme operators, in light of successive increases in the policy rate, lies in balancing the remuneration matrix of the card system so as to ensure efficiency and inclusion: keeping issuers encouraged to provide credit and services (even under high funding costs conditions) without excessively burdening merchants. In the Brazilian context, structurally lower interest rates would be beneficial to the card ecosystem, but as long as the Selic remains at elevated levels, mitigation measures such as caps on interchange fees (TIC), shorter settlement periods, and the promotion of competition will be crucial to ensure that the higher cost of money does not compromises the progress made in reducing payment costs for end users.

3.9 The Seasonal Nature of the Market

Empirical evidence shows that consumption in Brazil presents strong seasonal patterns throughout the year. In retail, marked seasonal fluctuations can be observed, with purchase peaks concentrated in December and May, corresponding respectively to Christmas and Mother's Day, traditionally the two dates with the highest sales volume. Conversely, February tends to register the lowest sales volume of the calendar, reflecting the shorter length of the month. Such behaviors confirm the cyclical character of Brazilian household consumption seasonality, driven by factors such as year-end festivities (13th salary and Christmas), seasonal promotions (such as Black Friday), and other commemorative celebrations, followed by periods of relative decline in consumption.

In this regard, seasonal variations in consumption produce effects on the acquiring sector, which is responsible for processing a large share of these transactions. Since the main source of revenue for acquirers consists of fees charged as a percentage of transacted volume (MDR), fluctuations in sales volume directly affect sector revenues. During consumption peaks, acquirers process a greater number of transactions, thereby generating more revenue. In the last quarter of 2023, for example, R$969 billion in card purchases were transacted. This amount corresponded to approximately 27% of the total volume of 2023, demonstrating the seasonal concentration of sales at the end of the year [25]. Conversely, at the beginning of the year, a decline in sales volume and electronic payments is typically observed, following the post-holiday contraction and other seasonal effects (such as lower commercial activity in January and February). In 2023, the first quarter accounted for 23% of the total card volume [25].

In summary, although seasonality in consumption mainly affects transaction volumes, possible adjustments in discount rates may be related to the adaptation to these cyclical effects, which must be taken into account for a better understanding of MDR trends.

Chapter 4

Methodology

A rigorous analysis of the effects of Pix on discount rates (MDR) in the acquiring market requires an appropriate methodology capable of isolating the influence of this variable from other cyclical and structural factors that affect pricing dynamics in the sector. This chapter outlines the methodological design employed in the analysis, the selection and treatment of variables, and the data sources used.

The model developed is based on the Interrupted Time Series (ITS) literature and aims to effectively represent the variations in discount rates over time, while meeting statistical requirements as well as the specificity of the phenomenon under study. Furthermore, the metrics used for the evaluation of the estimated models are presented, ensuring the robustness of the results discussed in the following chapter.

4.1 Modeling

Unlike a regulatory intervention or a one-time event, the adoption of Pix is a gradual process, so no abrupt effects on the behavior of the MDR variable are expected immediately after its introduction. In other words, this study is based on the following hypotheses:

1. Pix adoption grows approximately linearly over time;
2. Pix influences the credit MDR as its adoption increases;
3. Pix influences the debit MDR as its adoption increases.

Premise (1) can be verified and validated in Appendix A (indeed, we can state with statistical confidence that Pix use grew approximately linearly over time), while premises (2) and (3) are the subject of this analysis.

As Lopez Bernal et al. [36] establish in their framework for defining the impact model in an ITS analysis, it is important to understand the behavior of the intervention in order to correctly specify the experiment, checking, among other aspects, whether the intervention occurs gradually or abruptly. Modeling both the level effect and the slope effect of the series can be problematic for the experiment, especially if both have relatively small impacts in the same direction. This would reduce the significance of both variables and propagate collinearity effects.

Given this, the level variable X was not included in this study, in order to capture exclusively the influence of Pix on the trend of MDR evolution. This avoids degrading the explanatory power of the model. With this adjustment, the initial model proposed for the study is as follows:

$$MDR(t) = \beta_0 + \beta_1 \cdot TIME(t) + \beta_2 \cdot TIME\_AFTER\_PIX(t) + \varepsilon(t)$$

Where MDR is the dependent variable (average credit and debit MDR), TIME represents the progression of time and behaves like the T variable in the model studied by Linden [35], and TIME_AFTER_PIX represents the time elapsed since Pix was introduced until the end of the experiment.

However, as highlighted in the literature review, other relevant interventions occurred during the period and must be considered for accurate modeling. These are:

- Regulation on the cap of the debit card Interchange Fee (TIC);
- COVID-19 pandemic.

For this reason, both events will be included as control variables in the linear regression model of this study, with TETO_TIC_DEB representing the regulation on the debit card interchange fee and COVID_19 capturing the effects of the SARS-CoV-2 pandemic in Brazil. Although it is known that the pass-through of the interchange fee reduction to the MDR occurred gradually, and the pandemic's effects were not entirely abrupt, the waning effects of these interventions on MDR pricing are not fully understood in the literature. Therefore, these variables are modeled as dummies, avoiding loss of explanatory capacity due to erroneous assumptions about expected effects, as well as potential propagation of collinearity.

To capture seasonal effects of the market on MDR, quarterly dummies (Q1, Q2, Q3) are included in the model. The fourth quarter is omitted to avoid perfect collinearity among seasonal dummies, serving as the baseline for comparison, so that the included dummies represent the average effect of each quarter relative to Q4.

Finally, in order to analyze MDR dynamics, particularly in credit transactions, it is essential to account for the effects of the economy's policy interest rate. For this reason, a control variable was included to represent the quarterly average of the annualized SELIC rate.

It is important to note that, since MDR is already expressed as a percentage of the card transaction volume, no variables capturing inflation effects or related corrections were included in the model.

The inclusion of these control variables in the initially proposed model results in the following final specification for this study:

$$
\begin{aligned}
MDR(t) = \beta_0 &+ \beta_1 \cdot TIME(t) + \beta_2 \cdot TIME\_AFTER\_PIX(t) \\
&+ \beta_3 \cdot TETO\_TIC\_DEB + \beta_4 \cdot COVID\_19 \\
&+ \beta_5 \cdot SELIC + \beta_6 \cdot Q1 \\
&+ \beta_7 \cdot Q2 + \beta_8 \cdot Q3 + \varepsilon(t)
\end{aligned} \tag{4.1}
$$

By analyzing past data without manipulation of the variables, this experimental design is characterized as ex post facto, seeking to establish causal inference between the introduction of Pix and variations in MDR for credit and debit transactions.

4.2 Data Structure and Sources

For the analysis, quarterly data were collected, covering the period from the first quarter of 2011 through the second quarter of 2024. This was the time span and level of granularity in which information on average MDR was available from the Central Bank of Brazil [25]. These data can be found in the payment system statistics section on the Central Bank's website. For this study, two separate series were considered: one for credit MDR and another for debit MDR. In this manner, it would be possible to infer the effect of Pix on each variable individually.

As a result, the dataset was divided into 54 periods (four quarters over 13 and a half years). The quarters (Q) are naturally defined as January, February, and March for the first quarter (Q1); April, May, and June for the second (Q2); July, August, and September for the third (Q3); and October, November, and December for the fourth (Q4).

For the time variables, TIME and TIME_AFTER_PIX, each unit of time represents a three-month period. TIME evolves unit by unit from 1 to 54, spanning from Q1 2011 through Q2 2024. TIME_AFTER_PIX grows unit by unit from 1 to 15, covering Q4 2020 through Q2 2024. This is because the payment system was launched in November 2020 and remains in force to this day.

For the variables TETO_TIC_DEB and COVID_19, both behave as dummies. TETO_TIC_DEB takes the value 0 for the periods prior to Q4 2018, when Circular No. 3.887 entered into force, and 1 thereafter. COVID_19 assumes the value 1 from Q1 2020, when the Covid-19 pandemic was declared by the WHO and the first case of the disease was confirmed in Brazil [49], through Q2 2022, when the state of public health emergency was lifted [50]. The variable takes the value 0 in all other periods.

The quarterly dummies naturally take the value 1 in their respective quarters and 0 otherwise. As mentioned earlier, the dummy for Q4 is omitted from the model in order to avoid the classic problem of perfect multicollinearity, also known as the dummy variable trap [60].

For the treatment of the SELIC, whose historical series was only available on a daily basis from the Central Bank [59], the quarterly average was calculated, weighted by the number of days during which each rate remained in effect. This quarterly average was then assigned to each of the 54 periods in the study. The original series corresponds to code 1178 in the Central Bank of Brazil's Time Series Management System [59], under the title "Interest rate – Selic, annualized, 252-day basis."

The dataset used can be found in Appendix B.

4.3 Tool and Methods

Two linear regressions were performed using the Ordinary Least Squares (OLS) method, one for credit MDR and another for debit MDR. As the results of both regressions showed a Durbin–Watson index below 1.5, indicating positive autocorrelation of the residuals, the HAC technique was applied to correct the standard errors, mitigating potential violations of the assumptions of homoscedasticity and absence of autocorrelation.

The interface used was Jupyter Notebook, an interactive environment that allows the combination of code, visualizations, and annotations in a single document.

The programming language employed was Python, widely used in data science and applied econometrics, which offers a set of libraries for statistical analysis. The following libraries were used:

- pandas: for handling data in tabular structures;
- numpy: for mathematical and vector operations;
- statsmodels: for estimating statistical models, including OLS with robust corrections;
- matplotlib.pyplot: for generating graphical visualizations.

The complete code used to run the model on the platform is available in Appendix C.

4.4 Model Evaluation Metrics

To assess the robustness and statistical validity of the model developed, the following metrics will be primarily considered:

- Coefficient of determination (R^2): Evaluates the fit of the model, i.e., how much of the behavior of the dependent variable is explained by the model. An R^2 greater than 0.9 is expected for the model to be considered explanatory of MDR.
- Prob(F-statistic): Tests whether the model has at least one variable with a coefficient significantly different from zero. A Prob(F-statistic) below 0.05 is expected, indicating that at least one coefficient is statistically different from zero and reinforcing the overall usefulness of the model.

- Durbin–Watson (DW): Assesses the presence of serial autocorrelation among the regression residuals. The ideal value is 2. If regressions show values above 2.5 (negative autocorrelation) or below 1.5 (positive autocorrelation), the p-values of the model must be corrected using the standard error correction method known as HAC [61].

- Jarque–Bera (JB): Tests whether the residuals follow a normal distribution, an important condition for the validity of the statistical tests applied to the model. The critical JB value for $p = 0.05$ with 2 degrees of freedom is 5.99, meaning that values above this threshold indicate that residuals do not follow a normal distribution and the model must be corrected.

For the evaluation of explanatory variables, the following will be considered:

- p-value of the coefficients: Indicates the individual statistical significance of each variable. For a variable to be considered statistically relevant, its p-value must be below 0.05.

- VIF (Variance Inflation Factor): Measures the degree of multicollinearity of a variable with the others in the model. Variables with VIFs greater than 10 (except for the constant) should be addressed or excluded from the model to avoid compromising the stability of the estimates.

Chapter 5

Results

The application of the ITS regression models, as proposed in the previous section, produced robust estimates of the impact of Pix and other relevant variables on the average merchant discount rates (MDR) practiced in the Brazilian acquiring market. Separate models were employed for each function, both with standard errors corrected using the HAC (Newey–West) technique, due to the presence of positive autocorrelation identified through the Durbin–Watson test ($DW < 1.5$). The results obtained with both models, for credit MDR as well as for debit MDR, are shown in thie following sections.

5.1 Estimating The Impact of Pix on Credit MDR

The results of the OLS regression with HAC correction for the dependent variable credit MDR are presented in Figure 5.1.

With a coefficient of determination of $R^2 = 97.6\%$ and highly robust global statistical significance (Prob(F) < 0.001), we can state that the model exhibits excellent explanatory power for the variation in Credit MDR. Although the condition number, used as a proxy for overall multicollinearity, is above 100, the analysis of individual VIFs shows that the model is not compromised. All VIFs are controlled below 10, except for the constant, whose high collinearity is expected and harmless, since its coefficient is not directly interpreted. Given the historical series, some degree of collinearity among the remaining variables is also expected, especially with time-related variables, which is the case for TIME and TETO_TIC_DEB.

Regarding the residual diagnostics, the Jarque-Bera index presents a value of 0.44 (Prob(JB) = 0.802), well below the 5.99 threshold, ensuring that the errors follow an approximately normal distribution. Although the Durbin-Watson index indicates positive autocorrelation among the errors (DW = 1.052), which is also expected in time series, the HAC correction was applied to ensure the validity of p-values even in the presence of heteroscedasticity and autocorrelation.

It is also possible to observe in Figure 5.2 how the curve predicted by the model closely follows the actual Credit MDR curve throughout the period, reinforcing its explanatory power.

Dependent Variable	CREDIT_MDR	**R²**	0,976
Model	OLS	**Adjusted R²**	0,972
Method	Least Squares	**F-statistic**	375,1
Nº Observations	54	**Prob(F)**	<0,001
Df Residuals	45	**Log-Likelihood**	101,22
Df Model	8	**AIC**	-184,4
Covariance Type	HAC	**BIC**	-166,5

Variable	**Coef.**	**Std Error**	**T-value**	**P-value**	**IC 2.5%**	**IC 97.5%**	**VIF**
const	2,6865	0,032	84,124	0,000	2,622	2,751	35,7031
TIME	-0,0081	0,001	-6,958	0,000	-0,010	-0,006	5,3803
TIME_AFTER_PIX	-0,0016	0,002	-0,721	0,475	-0,006	0,003	3,7366
SELIC	0,0154	0,002	6,907	0,000	0,011	0,020	2,304
TETO_TIC_DEB	-0,1151	0,038	-3,064	0,004	-0,191	-0,039	5,5004
COVID_19	-0,141	0,020	-7,218	0,000	-0,180	-0,102	1,953
Q1	0,0124	0,019	0,645	0,522	-0,026	0,051	1,5118
Q2	-0,002	0,012	-0,172	0,865	-0,026	0,022	1,5118
Q3	-0,0091	0,014	-0,642	0,524	-0,038	0,020	1,4934

Omnibus	0,974	**Durbin-Watson**	1,052
Prob(Omnibus)	0,614	**Jarque-Bera (JB)**	0,44
Skew	-0,192	**Prob(JB)**	0,802
Kurtosis	3,221	**Cond. No.**	225

Figure 5.1: OLS regression results with HAC Credit MDR (Source: Developed by the author)

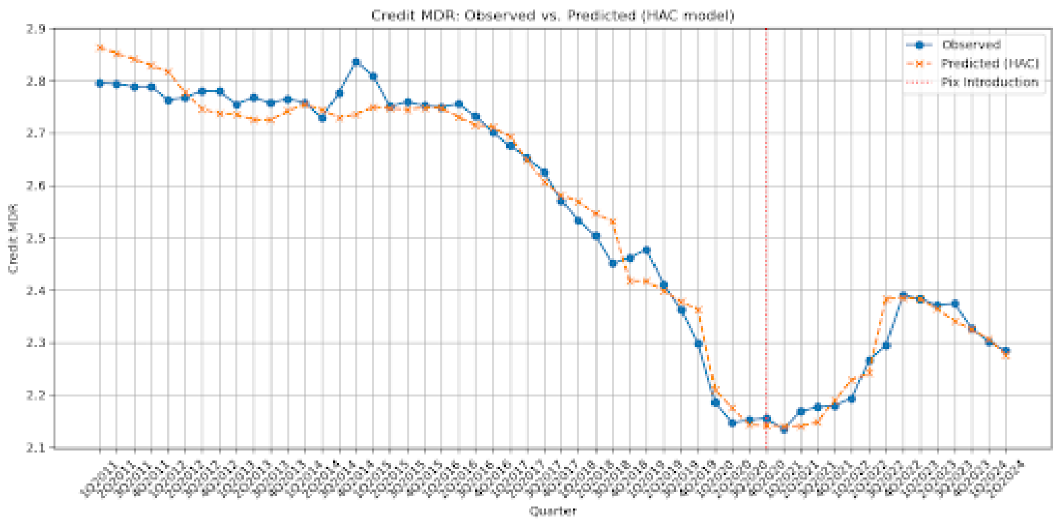

Figure 5.2: Credit MDR: observed vs. predicted (HAC model) (Source: Developed by the author)

Once the model is validated, the following interpretations can be made regarding the explanatory variables:

- Constant: Represents the estimated value of the Credit MDR when all explanatory variables in the model are equal to zero (2.69%). However, since some of these variables, such as TIME and SELIC, never assume a value of zero during the analyzed period, the constant does not have a direct or realistic economic interpretation. Still, its inclusion is essential for the proper fit of the model, ensuring that residuals are minimized and that the coefficients of the other variables are correctly estimated.

- TIME: The coefficient associated with TIME is negative and statistically significant (coef. = –0.0081; $p < 0.001$), indicating that the Credit MDR shows a downward trend over time. In each quarter, MDR is estimated to decrease by 0.81 basis points (0.0081%), disregarding the effects of the other variables in the model. This trend may reflect long-term structural factors in the Brazilian payments sector, such as economies of scale, technological innovation, and increased competition among banks and acquirers. The inclusion of TIME in the model plays a fundamental role within the ITS framework by allowing the use of the secular trend of the series as a counterfactual for assessing the effects of Pix and other interventions.

- SELIC: The SELIC coefficient is positive and statistically significant (coef. = +0.0154; $p < 0.001$), converging with the hypothesis that the Credit MDR indeed tends to follow fluctuations in SELIC. More specifically, each additional percentage point in SELIC is associated with an average increase of 0.0154 percentage points in the MDR, ceteris paribus. This result aligns with the literature and the operational logic of the sector: a higher SELIC increases the cost of capital for financial institutions, affecting the Interchange Fee (TIC) passed on to acquirers, who in turn tend to transfer this additional cost to merchants through the MDR.

- TETO_TIC_DEB: The estimated coefficient for TETO_TIC_DEB is negative and statistically significant (coef. = –0.1151; $p = 0.004 < 0.005$), indicating that the introduction of the regulatory cap on debit card Interchange Fees (TIC) also impacted the Credit MDR. Including this variable in the model captures the indirect effects of regulatory policy on debit caps, reflecting pricing adjustments in the credit function as well. Based on the estimates, the regulation's enforcement is associated with an average reduction of 0.1151 percentage points in the Credit MDR compared to the period prior to its implementation.

- COVID_19: The coefficient associated with COVID_19 is negative and highly significant (coef. = –0.1410; $p < 0.001$), indicating that during the pandemic period there was an average reduction of 0.1410 percentage points in the

Credit MDR compared to other periods. This result is consistent with the expected effects of the health crisis on the payments sector. In addition to triggering a generalized economic crisis and demanding strategic repositioning from companies, especially small and medium-sized merchants, the pandemic significantly accelerated retail digitalization and transformed the transaction mix, boosting the share of e-commerce and digital payment methods (SEBRAE, 2022). The model's results suggest that this generated structural effects on Credit MDR pricing, drastically reducing it during the period.

- Q1, Q2, Q3: The results for the quarterly variables Q1, Q2, and Q3 indicate that none of the dummies are statistically significant, with p-values of 0.522 for Q1, 0.865 for Q2, and 0.524 for Q3. This suggests that, conditional on the other variables in the model, there is no robust evidence that Q1, Q2, or Q3 exhibit systematically different behaviors from Q4 with respect to Credit MDR variation. In other words, quarterly seasonality does not appear to exert a significant influence on aggregate Credit MDR pricing, at least not in isolation.

- TIME_AFTER_PIX: The variable TIME_AFTER_PIX was included in the model to capture possible changes in the slope of the Credit MDR trend following the introduction of Pix in November 2020. However, the estimated coefficient (–0.0016), besides being small, is not statistically significant ($p = 0.475$), indicating that there is no robust evidence that Pix has accelerated (or decelerated) the downward trend of the Credit MDR in the period following its adoption, at least not in a statistically detectable way after controlling for the other variables. This may be related to the fact that Pix primarily operates as a substitute for cash and debit transactions, particularly for immediate and lower-value payments, rather than for installment-based credit transactions.

The evaluation of coefficients and p-values of the explanatory variables for the Credit MDR suggests that the main forces shaping its behavior during the analyzed period are more strongly linked to structural and institutional factors (such as SELIC, the pandemic, and regulation) than to cyclical or seasonal patterns.

Furthermore, the lack of significance of the variable associated with Pix adoption indicates that the new payment tool does not bring structural changes to the trajectory of the Credit MDR. This may be due to the fact that Pix's central features (availability, gratuity, and instantaneity) do not fully replace the demands of merchants and consumers when using the credit function. Credit cards offer advantages such as deferred payment, installment plans, and bill management, which Pix has not replicated yet, in addition to frequently offering rewards programs and benefits linked to their use.

As a result, there is no evidence that Pix currently acts as a competitive substitute for the credit function, which helps sustain the bargaining power of acquirers vis-à-vis merchants. Thus, it can be concluded that Pix does not generate relevant competitive pressure on the acceptance of credit cards by acquirers in the short and medium term.

Dependent Variable	MDR_DEBIT	**R²**	0,986
Model	OLS	**Adjusted R²**	0,983
Method	Least Squares	**F-statistic**	571,1
N° Observations	54	**Prob(F)**	1,36E-42
Df Residuals	45	**Log-Likelihood**	126,77
Df Model	8	**AIC**	-235,5
Covariance Type	HAC	**BIC**	-217,6

Variable	**Coef.**	**Std Error**	**T-value**	**P-value**	**IC 2.5%**	**IC 97.5%**	**VIF**
const	1,5844	0,017	94,94	0,000	1,551	1,618	35,7031
TIME	-0,0052	0,001	-7,64	0,000	-0,007	-0,004	5,3803
TIME_AFTER_PIX	-0,0081	0,002	-4,474	0,000	-0,012	-0,004	3,7366
SELIC	0,0027	0,001	2,119	0,040	0,000	0,005	2,304
TETO_TIC_DEB	-0,1476	0,026	-5,785	0,000	-0,199	-0,096	5,5004
COVID_19	-0,0796	0,015	-5,277	0,000	-0,110	-0,049	1,953
Q1	0,0215	0,011	1,896	0,064	-0,001	0,044	1,5118
Q2	-0,0066	0,008	-0,844	0,403	-0,022	0,009	1,5118
Q3	-0,0117	0,008	-1,383	0,174	-0,029	0,005	1,4934

Omnibus	3,215	**Durbin-Watson**	1,139
Prob(Omnibus)	0,2	**Jarque-Bera (JB)**	2,704
Skew	0,158	**Prob(JB)**	0,259
Kurtosis	4,05	**Cond. No.**	225

Figure 5.3: OLS regression results with HAC Debit MDR (Source: Developed by the author)

5.2 Estimating The Impact of Pix on Debit MDR

The results of the OLS regression with HAC for the dependent variable Debit MDR are presented in Figure 5.3.

With a coefficient of determination $R^2 = 98.6\%$ and highly robust overall statistical significance (Prob(F) < 0.001), we can state that the model exhibits excellent explanatory power for the variation in debit MDR. The Condition Number (225), although above 100, does not compromise the model. The analysis of the VIFs shows that all values are below 10, with the exception of the constant (VIF 35), whose multicollinearity is expected and irrelevant, since its coefficient is not interpreted directly. As with the credit model, higher VIF values for time-related variables (such as TIME and TETO_TIC_DEB) are expected in time series and do not indicate structural problems.

Regarding the residual diagnostics, the Jarque-Bera test (JB = 2.704; Prob = 0.259) indicates that the residuals follow an approximately normal distribution, since the JB statistic is below the threshold of 5.99 for 95% confidence. The Durbin-Watson index (DW = 1.139) reveals the presence of positive autocorrelation among residuals, a typical behavior in time series data. However, the model was adjusted with robust standard error corrections using the HAC method, ensuring the validity of the significance tests even in the presence of heteroskedasticity and autocorrelation.

The model's performance can also be visually examined in Figure 5.4 through the close alignment between the predicted curve and the observed debit MDR values over

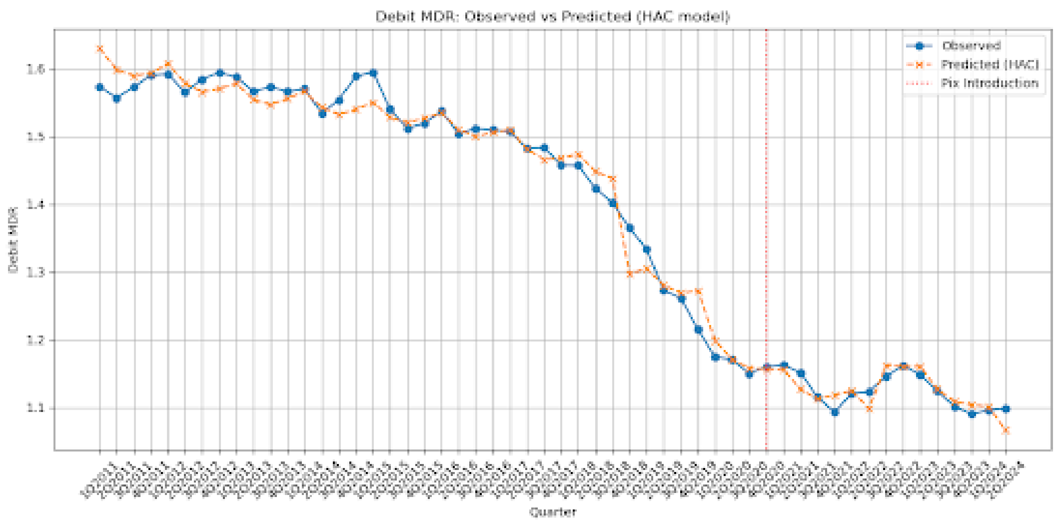

Figure 5.4: Debit MDR: observed vs. predicted (HAC model) (Source: Developed by the author)

the analyzed period, which reinforces its robustness and reliability for explanatory purposes.

After ensuring the model validation, we can make the following interpretations regarding the explanatory variables.

- Constant: The estimated constant of the model is approximately 1.58%, representing the expected debit MDR when all explanatory variables are equal to zero. As in the credit model, this interpretation has no direct economic validity, since variables such as TIME and SELIC never assume a null value within the analyzed period. Nevertheless, its inclusion is essential for the adjustment of the model, as it ensures the minimization of residuals and allows the correct estimation of the coefficients of the other variables.

- TIME: The coefficient of the TIME variable is negative and statistically significant (coef. $= -0.0052$; $p < 0.001$), suggesting that the debit MDR has a downward trend over time. It is estimated that, each quarter, the MDR decreases by approximately 0.52 basis points (0.0052%), controlling for the other variables in the model. Such behavior can be explained by structural phenomena observed in the Brazilian payments sector, such as increased operational efficiency, technological advances, and greater competition among acquirers. Furthermore, the TIME variable is fundamental in the context of ITS modeling, serving as the counterfactual basis for the analysis of structural changes after interventions such as the introduction of Pix.

- SELIC: The coefficient of the SELIC variable is positive and statistically significant (coef. $= +0.0027$; $p = 0.040$), although its effect is less pronounced than in the credit MDR model. Each percentage point increase in SELIC is associated with an increase of approximately 0.27 basis points (0.0027%) in the debit MDR, *ceteris paribus*. This suggests that even in the debit segment, where terms are shorter and credit risk is lower, the cost of capital affects pricing, albeit more modestly.

- TETO_TIC_DEB: The TETO_TIC_DEB variable has a negative and highly significant coefficient (coef. = –0.1476; $p < 0.001$), confirming the expectation that the regulatory reduction of the Debit Interchange Fee (TIC) directly impacted the debit MDR. The estimate suggests that the regulation on the interchange fee cap generated an average decrease of 0.1476 percentage points in the debit MDR. This result highlights the relevant role of regulatory policy on the sector's pricing structure and shows that acquirers partially pass on the reduction in TIC to merchants.

- COVID_19: The coefficient of the COVID_19 variable is negative and statistically significant (coef. = –0.0796; $p < 0.001$), indicating that the pandemic period was associated with an average reduction of 0.0796 percentage points in the debit MDR. This result aligns with the expected effects of the pandemic context: increased use of digital channels, changes in consumption profiles, and reduced bargaining power of acquirers in a scenario of economic crisis and retail transformation. These factors appear to have contributed to a structural reduction in MDR margins, including in debit.

- Q1, Q2, Q3: The seasonal variables representing quarters Q1, Q2, and Q3 did not show robust statistical significance, with p-values of 0.064, 0.403, and 0.174, respectively. This suggests that, controlling for the other variables in the model, there is no evidence that quarters Q1, Q2, or Q3 differ systematically from the fourth quarter (the reference category) in terms of debit MDR variation. Thus, no relevant seasonal quarterly effects are identified in the debit MDR.

- TIME_AFTER_PIX: The TIME_AFTER_PIX variable has a negative and statistically significant coefficient (coef. = –0.0081; $p < 0.001$), indicating that after the introduction of Pix, the downward trend of the debit MDR intensified. This means that, from Pix adoption onward, the slope of the MDR curve became steeper, with an additional reduction of 0.81 basis points (0.0081%) per quarter. This result is consistent with the hypothesis that Pix, as it consolidated itself as an efficient and free alternative for real-time cash payments, began exerting greater competitive pressure on debit cards.

The evaluation of coefficients and p-values for the explanatory variables of the debit MDR also suggests that the main factors influencing debit MDR in the analyzed period were structural and institutional changes in the payments market (such as Pix, the pandemic, and regulation), rather than cyclical seasonal patterns.

Moreover, the presence of statistical significance associated with the adoption of Pix indicates that the tool exerts competitive pressure on the acceptance of debit cards, compelling acquirers to reduce MDR prices for this function. This can be explained by the fact that Pix replicates most of the functionalities provided by debit cards, such as immediate payment, 24/7 availability, and merchant gratuity. This strengthens merchants' bargaining power vis-à-vis acquirers, who may encourage customers to pay with Pix instead of debit cards.

Thus, we can conclude that Pix generates relevant competitive pressures on the acceptance of debit cards by acquirers in the short and medium term. Its accumulated effect can be estimated through the following calculations:

$$\text{Absolute effect} = 0.0081 \times 15 = 0.122$$

Where –0.0081 is the coefficient of the variable TIME_AFTER_PIX and 15 is the number of quarters in the period after the introduction of Pix (Q4 2020 to Q2 2024).

$$\text{Relative effect} = \frac{-0.122\%}{1.22\%} = -10\%$$

Where –0.122% is the accumulated absolute effect of Pix on the debit MDR over the 15 quarters, and 1.22% is the debit MDR value in the last period of the experiment (Q2 2024) corrected by the absolute effect (1.1% + 0.122%). This is equivalent to stating that this would be the counterfactual debit MDR in Q2 2024 in a scenario without Pix introduction.

Therefore, over a period of 15 quarters, it is estimated that Pix reduced the average debit MDR by approximately 10%. Considering the 97.5% confidence intervals, this value could range between 5.17% and 14.1%.

Chapter 6

Conclusion

This study aimed to quantitatively estimate the impact of Pix on merchant discount rates (MDR), which constitute the main source of revenue in the acquiring services sector. By applying the Interrupted Time Series (ITS) methodology, it was possible to reach statistically significant conclusions regarding Pix's influence on MDR trajectories, allowing us to gain a deeper understanding of how Pix is contributing to reshaping the payments market in Brazil. This chapter aims to present a synthesis of the results obtained from the experiment, as well as to discuss the implications that this phenomenon brings to companies and institutions participants of the acquiring market in Brazil. Finally, the main limitations of the study will be outlined, along with possible paths for future developments.

6.1 Synthesis of Results

The econometric analyses conducted in this study allow us to identify contrasting effects of Pix on credit and debit merchant discount rates (MDR). In the case of credit, the results of the Interrupted Time Series (ITS) regression model did not reveal a statistically significant impact associated with the adoption of Pix. This is because, for this function, the post-intervention trend variable (TIME_AFTER_PIX), included to capture potential changes in the slope of the series from Q4 2020 onward, displayed an estimated coefficient close to zero (0.0016) and lacking statistical significance ($p = 0.475$). For this reason, there is no empirical evidence that Pix accelerated (or decelerated) the historical downward trend of credit MDR.

This can be explained by the fact that the core features of Pix (speed, availability, and zero cost) do not fully meet the demand of credit card users. In practice, credit cards offer other advantages that preserve their differentiation from Pix. Chief among these are deferred payments and installment options, as well as the benefits typically linked to credit card usage, such as rewards programs, cashback, and others. In this sense, the adoption of Pix does not, for now, appear to be a relevant factor driving negotiations between merchants and acquirers over credit MDR. Instead, variations in the SELIC rate or structural events such as the pandemic and regulatory changes provide a more robust explanation for this dynamic.

On the other hand, for debit MDR, the results showed a clear and significant impact stemming from the implementation of Pix. Empirical evidence indicates that from Q4 2020 onward, debit MDR exhibited a negative slope attributable to the increasing adoption of Pix. The coefficient associated with the TIME_AFTER_PIX variable was negative and significantly different from zero ($p < 0.001$), quantifying an additional reduction of approximately 0.0081% (0.81 basis points) per quarter in debit MDR compared to the pre-Pix trend. Aggregating this effect, it was estimated that over the 15 full quarters following the introduction of Pix (from Q4 2020 to Q2 2024), this change in slope implied an absolute reduction of approximately 0.122% in the average debit MDR, relative to the level expected had the prior trend persisted. In relative terms, this corresponds to a decline of about 10% (with confidence intervals between 5.17% and 14.17% at the 97.5% level) in debit MDR. It is important to recall that the MDR is a composite rate, with only part of it accruing to the acquirer, also known as net MDR, obtained after subtracting the interchange fee (TIC). Given that the TIC in the last quarter of the analyzed period was 0.48% and the MDR was 1.1% [25], this cumulative 0.122% impact corresponds to nearly 20% of the net MDR in the last period, which underscores the financial risk that Pix poses to acquirers.

In practical terms, this indicates that Pix has positioned itself as a substitute for debit payment instruments in the market, granting merchants greater bargaining power in negotiations with acquirers and pressuring the latter to gradually reduce fees charged for debit transactions in order to remain competitive. This is consistent with the fact that Pix already replicates the main functions of debit card payments (immediate transfer and 24/7 availability) at lower cost, making it a useful tool for non-recurring and low-value payments. Considering that debit MDR was an important source of recurring revenue, although already on a historical downward trajectory, the acceleration of this decline through Pix adoption threatens the long-term sustainability of acquirers' revenues. The competitive pressure triggered by Pix on debit transactions translates into lower unit profitability and potentially reduced card transaction volumes, as a portion of sales migrates to the new payment modality.

6.2 Strategic Implications for Companies in The Sector

This scenario, which points to a downward trend in debit revenue for acquirers, suggests that companies in the sector must undergo a strategic review to ensure financial sustainability and long-term competitiveness. Recent market developments corroborate this analysis. The delisting of Getnet in 2022 and Cielo in 2024 illustrate, in practice, the strategic reaction of incumbent firms to the new competitive environment: repositioning, restructuring of revenue models, and a stronger focus on diversification.

In response to this new context, one of the main strategies adopted by acquirers has been the incorporation of Pix and its functionalities into their product portfolios. Examples include:

- Pix QR Code on POS terminals: Payment machines now allow Pix transfers through QR codes generated directly on the device's screen. The payment is credited instantly to the merchant's account, with a fee applied to the transaction. This demonstrates a strategic adaptation by acquirers to monetize the new tool.

- Batch Pix and payroll via Pix: Many small businesses pay employees via Pix as a practical and low-cost transfer method. To meet this demand, banks and acquirers have incorporated batch Pix functionality, enabling multiple transfers simultaneously. While this may or may not incur fees for corporate clients, it encourages business owners to maintain balances in their accounts, generating float revenues for financial institutions.

- Pix with credit: Financial institutions have introduced "Pix with credit" or "guaranteed Pix," a feature that allows users to split or defer Pix payments using their credit card or bank account limit. Typically, a fee is charged on the total transfer amount, representing yet another revenue stream. This functionality also signals deeper integration between Pix and credit products. Through this strategy, for instance, Nubank ended 2023 with 13.6 million customers using Pix linked to their credit card.

Beyond integrating Pix into their ecosystems, acquirers must also prioritize and expand their product portfolios beyond payment processing. Instead of relying solely on card transaction MDR, companies should expand into higher value-added services that address broader merchant needs, such as access to credit and business management tools. This includes offering integrated financial solutions such as working capital loans, accounts receivable management, and receivables anticipation, as well as sales management platforms, including point-of-sale software, inventory control, invoicing, and more. These initiatives enhance the acquirer's value proposition, generate new revenue sources complementary to transaction fees, and increase the share of merchants' financial flows managed within their ecosystem.

The strategic implications of Pix for the payments sector are profound. They demand innovation, agility, and flexibility from acquirers and other players, who must adapt to a new paradigm where competitive advantage lies less in charging transaction fees and more in providing comprehensive, convenient, and low-cost solutions to their clients.

6.3 Limitations and Evolutions for Future Research

The findings of this study bring valuable perspectives for future investigations in the field of payment economics and banking competition. However, despite its contributions, it is important to acknowledge some limitations of the analysis conducted.

First, for this initial version of the impact model, we opted to simplify the behavior of variables with complex and not yet fully explored effects, such as TETO_TIC_DEB and COVID_19. As demonstrated by the Central Bank of Brazil Special Study No. 106/2021 (2021), Circular 3.887 (which capped the average debit interchange fee at 0.5%) had an almost immediate effect on interchange fees, but the pass-through of this reduction to the MDR occurred gradually. In the first quarter after the intervention, only 16.9% of the reduction was passed through, reaching 64.3% by Q1 2020. Thus, the regulatory effect is expected to unfold over time, eventually plateauing once the full cost reduction is absorbed. Capturing this dynamic in the model would require a deeper understanding of the pass-through curve and the inclusion of additional terms, which would increase collinearity. Particularly given the presence of other concurrent time variables such as TIME, TIME_AFTER_PIX, and COVID_19. A possible evolution of this research would be to smooth the effect of the interchange cap on the MDR trajectory, meeting these conditions without compromising the model.

Similarly, the pandemic's impact on MDR is unlikely to have been completely abrupt, as the market gradually adapted to sanitary measures, both at the onset and at the end of the crisis. Some effects persisted even after the pandemic, such as the adoption of contactless payments and e-commerce, as discussed in the literature review. With careful attention to potential collinearity, future research could incorporate a more detailed curve of the pandemic's impact on payment methods, thereby improving the model's fit to observed behavior.

Another limitation relates to the trajectory of Pix adoption. As shown in Appendix A, Pix adoption followed an almost linear trend over time. However, should more recent data (unavailable at the time of this study) reveal an acceleration or deceleration in adoption, the model's validity may be compromised. In that case, assessing Pix's impact based on the total transaction volume rather than on a simple time-since-introduction variable might prove more accurate. The choice of TIME_AFTER_PIX over quarterly transaction volumes in this study was made for the sake of simplification.

Additionally, some explanatory variables highlighted in the literature review were not included as controls. One example is Law 13.455/17, which allowed merchants to set differentiated prices depending on the payment method. Under this regulation, merchants can pass on the costs of payment acceptance to customers, encouraging them to use cheaper methods such as Pix. However, it remains unclear in the literature whether this increased bargaining power materially affected negotiations and the pricing of discount rates. Deeper scientific inquiry into this legislation would pave the way for incorporating its effects into future models.

Likewise, Pix with credit is emerging as an innovation that could blur the boundaries between Pix and credit cards. Investigating the effects of "Pix on credit" on consumer and merchant behavior will be crucial to understanding the extent to which this feature cannibalizes credit card usage, thus exerting pressure on credit MDR as well. Future studies may quantify these effects as more recent data become available, offering a more complete view of the "second wave" of disruption brought by Pix.

Another important limitation stems from data availability. The reliance on publicly available aggregated market data (average MDRs per payment function) may obscure heterogeneity across acquirers and merchant segments. Each acquirer has distinct cost structures and commercial strategies, as well as varied client profiles (by size, sector, and transaction volume). While aggregated data are suitable for capturing overall industry trends, they do not allow for isolating Pix's impact on specific subgroups. Disaggregated data would help identify vulnerabilities and competitive asymmetries. For instance, larger acquirers with scale and diversified portfolios may better absorb Pix's pressure compared to smaller firms focused exclusively on cards. Similarly, certain merchant segments (e.g., microentrepreneurs seeking to avoid fees) may adopt Pix more intensively, while others (e.g., sectors reliant on installment payments) may remain dependent on cards, resulting in differentiated impacts across acquirers.

Finally, limitations inherent to time-series econometric studies also apply, such as potential biases from omitted variables (even though the main known events were included, unobserved factors may still influence MDR) and the impossibility of establishing perfect causality in a non-experimental setting. These caveats do not invalidate the results obtained but rather delimit the scope of the conclusions and call for caution in generalizing them indefinitely.

6.4 Final Considerations

In summary, the results obtained confirm one of the central hypotheses of this study: Pix has indeed contributed to the reduction of the Merchant Discount Rate, threatening the traditional sources of revenue in the acquiring sector, especially with respect to debit products. This influence manifests itself asymmetrically across functions (strong in debit and, so far, not significant in credit), highlighting how the nature of innovation can affect different segments in distinct ways.

In the short and medium term, the debit card segment has experienced a significant loss of profitability due to competition from Pix, while the credit card segment has maintained relative resilience, thanks to specific characteristics that have not yet been replicated by the new technology. In the long term, however, the scenario remains uncertain. The accelerated pace of Pix adoption and the emergence of features such as Pix on Credit indicate that the boundaries between payment methods are becoming increasingly blurred, and no niche is entirely immune to the transformations underway.

For established firms, this represents a need for continuous adaptation and strategic innovation, under the risk of seeing their revenue streams eroded in a market that is becoming more dynamic, competitive, and cost-efficiency driven. Ultimately, the consolidation of Pix as an omnipresent and democratic payment infrastructure reflects the Central Bank's objectives of making financial transactions faster, cheaper, and more accessible to the entire population.

This new reality presents considerable challenges, but also opportunities for acquirers and other market participants. The challenges of readjusting business models and seeking new ways to generate value, and the opportunities to expand services, foster financial inclusion, and explore innovations in a rapidly evolving ecosystem. It is hoped that the discussions and evidence presented in this study will contribute to a better understanding of Pix's impact on the payments sector and serve as a foundation for strategic decisions and future research, in an environment where the capacity for adaptation and reinvention will be decisive for the sustainability of acquiring companies in Brazil.

Appendix A

Empirical Analysis of Pix Adoption Curve

The purpose of this appendix is to demonstrate that the adoption trajectory of Pix exhibits an approximately linear behavior over time, thereby validating hypothesis (1) presented in the Modeling section (in Methodology) and justifying the use of the variable TIME_AFTER_PIX, with its characteristic behavior, in the main analysis of this study.

To this end, an OLS linear regression will be performed, employing the HAC technique to correct standard errors, on the volume transacted via Pix (in BRL) with respect to time. The dependent variable will be called PIX and will represent the total volume transacted via Pix in Brazilian reais for each quarter, from Q4 2020 to Q2 2024. The sole explanatory variable used will be TIME_AFTER_PIX, which increases unitarily from 1 to 15 across the 15 quarters of this same time frame. Accordingly, the final formula of the linear regression can be described as:

$$\text{PIX}(t) = \beta_0 + \beta_1 \cdot \text{TIME\_AFTER\_PIX}(t) + \epsilon(t)$$

The data used for this analysis are available in Appendix C, having been extracted from the official website of the Central Bank of Brazil [25], and the software employed was Jupyter Notebook, using the Python programming language. The code for performing the linear regression demonstrated here is provided in Appendix D.

- Coefficient of determination (R^2)
- Prob(F-statistic)
- Durbin-Watson (DW)
- Jarque-Bera (JB)
- p-values of the coefficients
- VIF (Variance Inflation Factor) of the variables

Dependent Variable	PIX	**R²**	0,985
Model	OLS	**Adjusted R²**	0,983
Method	Least Squares	**F-statistic**	693,8
N° Observations	15	**Prob(F)**	1,15E-12
Df Residuals	13	**Log-Likelihood**	-413,25
Df Model	1	**AIC**	830,5
Covariance Type	HAC	**BIC**	831,9

Variable	Coef.	Std Error	T-value	P-value	IC 2.5%	IC 97.5%	VIF
const	-2,74E+11	9,96E+10	-2,751	0,006	-4,69E+11	-7,88E+10	4,428571
TIME_AFTE R_PIX	4,12E+11	1,56E+10	26340	0,000	-3,81E+11	4,42E+11	1,000000

Omnibus	0,69	**Durbin-Watson**	1,002
Prob(Omnibus)	0,708	**Jarque-Bera (JB)**	0,137
Skew	0,234	**Prob(JB)**	0,934
Kurtosis	2,991	**Cond. No.**	19,3

Figure A.1: OLS regression results with HAC for Pix (Source: Developed by the author)

The results obtained from the regression are presented in Figure A.1 above.

Regarding the explanatory power of the model, the R^2 indicates that 98.5% of the variation in Pix transaction volume can be explained solely by the variable TIME_AFTER_PIX, which demonstrates the robustness of the model. This is further corroborated by the highly significant F-statistic (p close to zero).

Aligned with this, the coefficient of the variable TIME_AFTER_PIX is also highly significant with $p < 0.001$, indicating a linear growth trend in transaction volume, with an increase of approximately BRL 412 trillion per quarter since the launch of Pix (considering intervals of BRL 381 to BRL 442 trillion with 97.5% statistical confidence).

Regarding the residual diagnostics, the Jarque-Bera test does not reject the hypothesis of normality of the residuals ($p = 0.934$), indicating that the residuals follow an approximately normal distribution, despite the small sample size ($n = 15$), which should be taken into consideration. The Durbin-Watson value close to 1 suggests slight positive autocorrelation, but this is mitigated by the use of HAC-corrected standard errors, and the model's condition number (Cond. No. 19.3) falls within a safe range, indicating no multicollinearity issues (particularly given that only one explanatory variable was used in the model).

The alignment of the observed Pix adoption curve with that predicted by the model can also be visually verified in Figure A.2.

Based on the analysis conducted in this appendix, it is empirically confirmed that the adoption trajectory of Pix exhibits an approximately linear behavior over the quarters following its launch. The statistical significance of the coefficients, combined with the high R^2, validates Hypothesis (1) proposed in the Methodology section: the volume transacted via Pix grows linearly over time. Accordingly, the variable TIME_AFTER_PIX can be considered statistically robust for capturing the effect of the increasing adoption of Pix in the main analysis of this study.

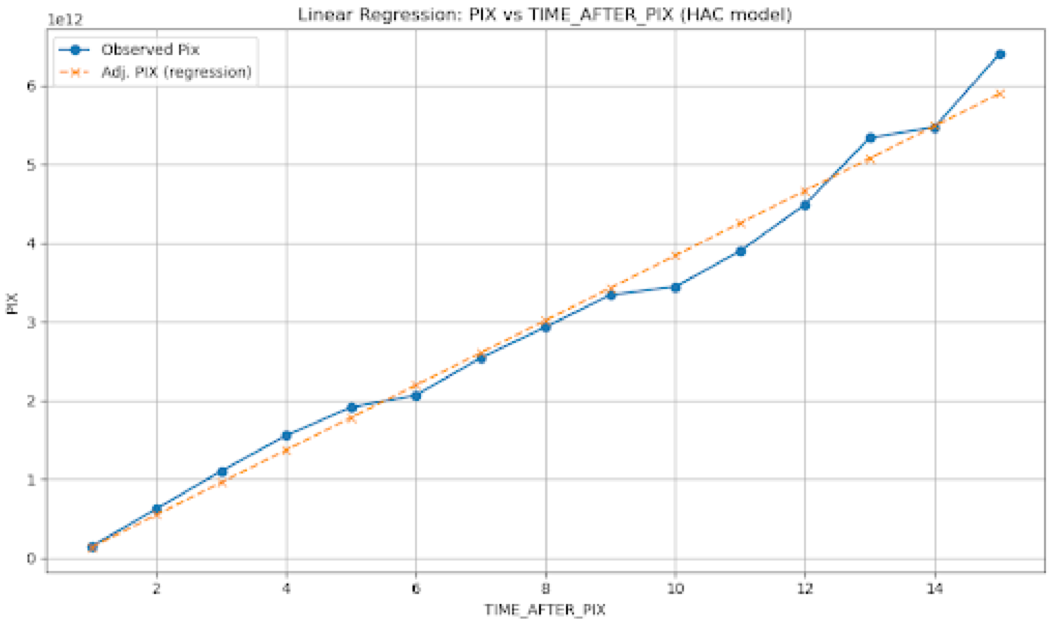

Figure A.2: PIX vs TIME_AFTER_PIX: observed vs. predicted (HAC model) (Source: Developed by the author)

Appendix B

Database

Database constructed based on data provided by the Central Bank for linear regression of credit and debit MDR, as well as the one present in appendix A, can be found in the following public link: `https://docs.google.com/spreadsheets/d/1XDRbHi1bOKlv7miXAg-7QsqhOZZiOYza/edit?gid=1197332726#gid=1197332726`

Appendix C

Source Code for MDR Regression

Source code used for performing the linear regression of credit and debit MDR in Python:

Listing C.1: Linear regression of Debit MDR in Python

```python
# import libraries
import pandas as pd
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
import matplotlib.pyplot as plt

# Upload sheet file
df = pd.read_excel(r"C:\Users\Matheus\Downloads\BASE DE DADOS - ITS (1).xlsx", sheet_name="Base de Dados")

# Define dependent variable
y = df["DEBIT_MDR"]

# Define explanatory variables
X = df[["TIME", "TIME_AFTER_PIX", "SELIC", "TETO_TIC_DEB", "COVID_19",
        "Q1_DUMMY", "Q2_DUMMY", "Q3_DUMMY"]]
X = sm.add_constant(X)

# Adjust OLS model
model = sm.OLS(y, X).fit()

# Apply HAC
model_hac = model.get_robustcov_results(cov_type='HAC', maxlags=1)

# Print results
print(model_hac.summary())
```

```

# Calculate VIFs
vif_data = pd.DataFrame({
    "Variável": X.columns,
    "VIF": [variance_inflation_factor(X.values, i) for i in
    range(X.shape[1])]
})
print(vif_data)

# Chart Observed vs Predicted
plt.figure(figsize=(12, 6))
plt.plot(df["QUARTER"], y, label="Observed", marker='o')
plt.plot(df["QUARTER"], model_hac.fittedvalues, label="
    Predicted (HAC)", linestyle='--', marker='x')
plt.axvline(x=df[df["TIME_AFTER_PIX"] == 1].index[0], color='
    red', linestyle=':', label="Pix Introduction")
plt.xticks(rotation=45)
plt.xlabel("Quarter")
plt.ylabel("Debit MDR")
plt.title("Debit MDR: Observed vs Predicted (HAC model)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

Listing C.2: Linear regression of Credit MDR in Python

```
import pandas as pd
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import
    variance_inflation_factor
import matplotlib.pyplot as plt

# Upload sheet file
df = pd.read_excel(r"C:\Users\Matheus\Downloads\BASE DE DADOS -
    ITS (1).xlsx", sheet_name="Base de Dados")

# Define dependent variable
y = df["CREDIT_MDR"]

# Define explanatory variables
X = df[["TIME", "TIME_AFTER_PIX", "SELIC", "TETO_TIC_DEB", "
    COVID_19",
        "Q1_DUMMY", "Q2_DUMMY", "Q3_DUMMY"]]
X = sm.add_constant(X)

# Adjust OLS model
model = sm.OLS(y, X).fit()

```

```python
# Apply HAC
model_hac = model.get_robustcov_results(cov_type='HAC', maxlags
    =1)

# Print results
print(model_hac.summary())

# Calculate VIFs
vif_data = pd.DataFrame({
    "Variável": X.columns,
    "VIF": [variance_inflation_factor(X.values, i) for i in
    range(X.shape[1])]
})
print(vif_data)

# Chart Observed vs Predicted
plt.figure(figsize=(12, 6))
plt.plot(df["QUARTER"], df["CREDIT_MDR"], label="Observed",
    marker='o')
plt.plot(df["QUARTER"], model_hac.fittedvalues, label="
    Predicted (HAC)", linestyle='--', marker='x')
plt.axvline(x=df[df["TIME_AFTER_PIX"] == 1].index[0], color='
    red', linestyle=':', label="Pix Introduction")
plt.xticks(rotation=45)
plt.xlabel("Quarter")
plt.ylabel("Credit MDR")
plt.title("Credit MDR: Observed vs. Predicted (HAC model)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

Appendix D

Source Code for Time After Pix Regression

Source code used for performing the linear regression of Pix over time in Python:

Listing D.1: Linear regression of Pix vs TIME_AFTER_PIX in Python

```
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import warnings

# Upload data
df = pd.read_excel(r"C:\Users\Matheus\Downloads\BASE DE DADOS -
    ITS (1).xlsx", sheet_name="Base de Dados")

# Filter and create a safe copy
df_filtered = df[(df['PIX'] != 0) & (df['TIME_AFTER_PIX'] != 0)
    ].copy()

# Define variables
y = df_filtered['PIX']
X = sm.add_constant(df_filtered['TIME_AFTER_PIX'])

# OLS regression with HAC
model = sm.OLS(y, X).fit(cov_type='HAC', cov_kwds={'maxlags':
    1})

# Print summary
print(model.summary())

# Add predicted values
df_filtered['PIX_predicted'] = model.predict(X)

# Plot chart
plt.figure(figsize=(10, 6))
plt.plot(df_filtered['TIME_AFTER_PIX'], df_filtered['PIX'],
```

```
    marker='o', label='Observed Pix')
plt.plot(df_filtered['TIME_AFTER_PIX'], df_filtered['
    PIX_predicted'], linestyle='--', marker='x', label='Adj. PIX
     (regression)', alpha=0.8)
plt.xlabel('TIME_AFTER_PIX')
plt.ylabel('PIX')
plt.title('Linear Regression: PIX vs TIME_AFTER_PIX (HAC model)
    ')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

Bibliography

[1] Stone. *Card Machine*. https://www.stone.com.br/maquina-de-cartao/. Accessed: 25 May 2025 (cit. on p. 1).

[2] Adriana Hernandez Perez and Claudia Bruschi. *The Payment Industry in Brazil: Recent Movements*. São Paulo: Insper, 2018 (cit. on pp. 1, 3, 6, 7, 9, 10, 19–21, 24).

[3] Claudemiro dos Santos Filho. "Customer-Centered Innovation and Building Competitive Advantages Through Competition for the Future: A Study of the Acquiring Market in Brazil". Professional Master's Dissertation, 79 pages. São Paulo: Fundação Getulio Vargas, Escola de Administração de Empresas de São Paulo, 2022 (cit. on pp. 2, 4, 8, 9).

[4] Central Bank of Brazil. *Pix Management Report: Conception and First Years of Operation (2020–2022)*. `https://www.bcb.gov.br/estabilidadefinanceira/pix`. Accessed: 25 May 2025. 2023 (cit. on pp. 2, 3, 23, 24).

[5] Central Bank of Brazil. *Pix: Instant Payments*. `https://www.bcb.gov.br/estabilidadefinanceira/pix`. Accessed: 25 May 2025 (cit. on p. 2).

[6] Central Bank of Brazil. *Statistical Addenda of the Brazilian Payment System – 2024*. `https://www.bcb.gov.br/estatisticas/spbadendos?ano=2024`. Accessed: 25 May 2025. 2024 (cit. on pp. 2, 13).

[7] Edson Santos. *Opinion: Pix and the End of the Hegemony of Cards*. Brazil Journal. Accessed: 25 May 2025, Available at: https://braziljournal.com/opiniao-o-pix-e-o-fim-da-hegemonia-dos-cartoes/. 2025 (cit. on pp. 2, 3).

[8] Gustavo Henrique Rodrigues Rocha. "The Impacts of Pix on the Brazilian Financial System (2020–2022)". Undergraduate thesis, 46 pages. Goiânia: Pontifícia Universidade Católica de Goiás, 2023 (cit. on pp. 3, 24).

[9] M. C. Sampaio and J. R. H. Ornelas. "Payment Technology Complementarities and Their Consequences on the Banking Sector: Evidence from Brazil's Pix". In: *Faster Digital Payments: Global and Regional Perspectives*. BIS Papers 152. Basel: Bank for International Settlements, 2024 (cit. on pp. 3, 24).

[10] Central Bank of Brazil. *Payment Arrangements*. `https://aprendervalor.bcb.gov.br/estabilidadefinanceira/arranjospagamento?ano=2023`. Accessed: 25 May 2025. 2023 (cit. on p. 4).

[11] Carlos Ragazzo. *Regulação de Meios de Pagamento*. 2nd ed. São Paulo, Brazil: Juruá Editora, 2023, p. 202. ISBN: 9786526307175 (cit. on p. 4).

[12] Natália Luiza Klein Saenger. "The Dematerialization of Money and the Evolution of Electronic Payment Methods in Brazil in the Face of Regulatory Changes Between 2010 and 2018". Undergraduate thesis, 90 pages. Porto Alegre: Universidade Federal do Rio Grande do Sul, Faculdade de Ciências Econômicas, 2019 (cit. on pp. 4–7).

[13] Rafael Pentagna Silvestre. "The Effect of the Creation of the Elo Brand on Fees Charged by the Brazilian Payment Industry". Master's Dissertation in Business Economics and Finance, 67 pages. Rio de Janeiro: Fundação Getulio Vargas, Escola de Pós-Graduação em Economia, 2019 (cit. on pp. 4, 6, 7).

[14] Ana Paula Schwenck. "Analysis of Regulatory Intervention and Antitrust Action on Entry Barriers in the Acquiring Sector from 2009 to 2017". Undergraduate thesis, 71 pages. Rio de Janeiro: Universidade Federal do Rio de Janeiro, Instituto de Economia, 2018 (cit. on pp. 5, 7, 9, 10).

[15] Senado Federal (Brasil). *Final Report of the Parliamentary Commission of Inquiry on Credit Cards*. Tech. rep. Brasília, DF: Senado Federal, 2018 (cit. on pp. 6, 9, 21).

[16] Administrative Council for Economic Defense (CADE). Department of Economic Studies. *CADE Notebooks: Payment Instruments Market*. `https://doi.org/10.52896/dee.cc2.019`. Accessed: 25 May 2025. 2019 (cit. on pp. 6, 7).

[17] C. F. S. Gomes and H. G. Costa. "Application of Multicriteria Methods to the Problem of Choosing Electronic Payment Models by Credit Card". In: *Production* 25.1 (Jan. 2015). Jan./Mar. 2015, pp. 54–68 (cit. on p. 7).

[18] Smithsonian Institution. *Diners Club Credit Card, United States, 1955*. https://www.si.edu/obje club-credit-card-united-states-1955:nmah_746975. Accessed: 25 May 2025 (cit. on p. 8).

[19] Olhar Digital. *Ancient Technologies: How the Carbon Credit Card Machine Worked*. https://olhardigital.com.br/2022/04/06/tira-duvidas/tecnologias-antigas-maquina-carbono-cartao-de-credito/. Accessed: 25 May 2025. Apr. 2022 (cit. on pp. 7, 8).

[20] REDUNIQ. *How Has the Automatic Payment Terminal Evolved Throughout History?* https://www.reduniq.pt/blog/como-evoluiu-o-terminal-de-pagamentos-automatico-ao-longo-da-historia/. Accessed: 25 May 2025 (cit. on p. 8).

[21] Central Bank of Brazil; Secretariat of Economic Law (Brazil); Secretariat of Economic Monitoring (Brazil). *Report on the Payment Card Industry*. 2010 (cit. on pp. 9, 18).

[22] Central Bank of Brazil. *Circular Letter No. 3.887 of March 26, 2018: Procedures for Reporting Interchange Fees*. https://www.bcb.gov.br/estabilidadefinanceira/exibenormativo?tipo=Carta%20Circular&numero=3887. Accessed: 25 May 2025. 2018 (cit. on p. 10).

[23] Central Bank of Brazil. *Circular No. 4.020 of November 30, 2020: Rules and Criteria for Payment Transaction Initiation Services within Pix*. https://www.bcb.gov.br/estabilidadefinanceira/exibenormativo?tipo=Circular&numero=4020. Accessed: 25 May 2025. 2020 (cit. on p. 10).

[24] Central Bank of Brazil. *Resolution BCB No. 246 of December 15, 2022: Requirements for Payment Arrangement Portability within the Brazilian Payment System (SPB)*. https://www.bcb.gov.br/estabilidadefinanceira/exibenormativo?tipo=Resolu%C3%A7%C3%A3o%20BCB&numero=246. Accessed: 25 May 2025. 2022 (cit. on pp. 10, 21).

[25] Central Bank of Brazil. *Statistical Data – First Semester 2024*. https://www.bcb.gov.br/content/estatisticas/spbadendos/Dados%20Estat%C3%ADsticos%202024S1.xlsx. Accessed: 25 May 2025, Excel file. 2024 (cit. on pp. 11–17, 31, 32, 35, 47, 52).

[26] InfoMoney. *PagSeguro, from UOL, Raises US$ 2.3 Billion in IPO in New York*. https://www.infomoney.com.br/mercados/pagseguro-do-uol-levanta-us-23-bilhoes-em-ipo-em-nova-york/. Accessed: 25 May 2025. Jan. 2018 (cit. on p. 11).

[27] Forbes Brasil. *Brazilian Stone Raises US$ 1.5 Billion in U.S. IPO*. https://forbes.com.br/negocios/2018/10/brasileira-stone-levanta-us-15-bi-em-ipo-nos-eua/. Accessed: 25 May 2025. Oct. 2018 (cit. on p. 11).

[28] Instituto Propague. *Payments Market in Data: 2021 Report. 3rd Edition*. https://institutopropague.org/wp-content/uploads/2022/06/Mercado-de-pagamentos-em-dados-Edicao-3-.pdf. Accessed: 25 May 2025. 2022 (cit. on pp. 14, 29).

[29] J. C. Rochet and J. Tirole. "Platform Competition in Two-Sided Markets". In: *Journal of the European Economic Association* 1.4 (2003), pp. 990–1029 (cit. on pp. 18–20).

[30] J. C. Rochet and J. Tirole. "Two-Sided Markets: An Overview". In: *Review of Network Economics* 3.2 (2004), pp. 90–109 (cit. on pp. 18, 19, 21).

[31] R. Schmalensee. "Payment Systems and Interchange Fees". In: *Journal of Industrial Economics* 50.2 (2002), pp. 103–122 (cit. on p. 19).

[32] J. C. Rochet and J. Tirole. *Cooperation among Competitors: Some Economics of Payment Card Associations*. Tech. rep. NBER Working Paper No. 8991. Cambridge: National Bureau of Economic Research, 2002 (cit. on pp. 19, 20).

[33] European Union. *Regulation (EU) No. 2015/751 of the European Parliament and of the Council of 29 April 2015 on Interchange Fees for Card-Based Payment Transactions*. Official Journal of the European Union, L 123, pp. 1–15, 19 May 2015. Accessed: 26 May 2025, Available at: https://eur-lex.europa.eu/eli/reg/2015/751/oj (cit. on p. 20).

[34] Transaction Resources. *Review of the Impact of Australian Payments Reforms*. Tech. rep. Melbourne: TransAction Resources Pty Ltd, Feb. 2011 (cit. on p. 20).

[35] A. Linden. "Conducting Interrupted Time-Series Analysis for Single- and Multiple-Group Comparisons". In: *The Stata Journal* 15.2 (2015), pp. 480–500 (cit. on pp. 21, 22, 34).

[36] J. Lopez Bernal, S. Soumerai, and A. Gasparrini. "A Methodological Framework for Model Selection in Interrupted Time Series Studies". In: *Journal of Clinical Epidemiology* 103 (2018). Accessed: 14 May 2025, pp. 82–91. DOI: `10.1016/j.jclinepi.2018.05.026` (cit. on pp. 21–23, 33).

[37] B. E. Huitema and J. W. McKean. "Design Specification Issues in Time-Series Intervention Models". In: *Educational and Psychological Measurement* 60 (2000), pp. 38–58 (cit. on p. 21).

[38] A. Linden and J. L. Adams. "Applying a Propensity-Score Based Weighting Model to Interrupted Time Series Data: Improving Causal Inference in Program Evaluation". In: *Journal of Evaluation in Clinical Practice* 17.6 (2011), pp. 1231–1238 (cit. on p. 21).

[39] D. K. Simonton. "Cross-Sectional Time-Series Experiments: Some Suggested Statistical Analyses". In: *Psychological Bulletin* 84 (1977). 1977a, pp. 489–502 (cit. on p. 21).

[40] D. K. Simonton. "Erratum to Simonton". In: *Psychological Bulletin* 84 (1977). 1977b, p. 1097 (cit. on p. 21).

[41] K. Bykov et al. "Interrupted Time Series Design in Health Research: A Tutorial". In: *BMC Medical Research Methodology* 21.1 (2021), pp. 1–11. DOI: `10.1186/s12874-021-01306-w` (cit. on p. 22).

[42] J. Lopez Bernal, S. Cummins, and A. Gasparrini. "Interrupted time series regression for the evaluation of public health interventions: a tutorial". In: *International Journal of Epidemiology* 46.1 (2017), pp. 348–355. DOI: `10.1093/ije/dyw098` (cit. on p. 22).

[43] A. K. Wagner et al. "Segmented Regression Analysis of Interrupted Time Series Studies in Medication Use Research". In: *Journal of Clinical Pharmacy and Therapeutics* 27.4 (2002), pp. 299–309 (cit. on p. 22).

[44] Marcela Ayres. *Brazil's Pix Payments Are Killing Cash. Are Credit Cards Next?* `https://www.reuters.com/business/finance/brazils-pix-payments-are-killing-cash-are-credit-cards-next-2024-04-02/`. Reuters, Accessed: 25 May 2025. Apr. 2024 (cit. on pp. 24, 25).

[45] J.-C. Rochet and J. Tirole. "Must-take Cards: Merchant Discounts and Avoided Costs". In: *Journal of the European Economic Association* 9.3 (2011), pp. 462–495. DOI: 10.1111/j.1542-4774.2011.01018.x (cit. on p. 26).

[46] J. Wright. "Why Payment Card Fees Are Biased Against Retailers". In: *The RAND Journal of Economics* 43.4 (2012), pp. 761–780 (cit. on p. 26).

[47] L. Rezende. "Why Regulate the Credit Card Interchange Fee in Brazil". Unpublished manuscript. 2019 (cit. on p. 26).

[48] Central Bank of Brazil. *Regulatory Assessment of the Introduction of Limits on Debit Card Interchange Fees*. Special Study No. 106. 2021 (cit. on p. 26).

[49] CNN Brasil. *5 Years of Covid-19: A Retrospective from the First Case to the End of the Emergency*. https://www.cnnbrasil.com.br/saude/5-anos-da-covid-19-relembre-o-historico-desde-1o-caso-ate-fim-da-emergencia/. Published: 31 Dec 2024. Updated: 11 Mar 2025. Accessed: 30 May 2025. Dec. 2024 (cit. on pp. 27, 35).

[50] Brazil. Ministry of Health. *After Two Years, the Public Health Emergency in Brazil Due to Covid-19 Comes to an End*. https://www.gov.br/saude/pt-br/assuntos/noticias/2022/maio/apos-dois-anos-chega-ao-fim-estado-de-emergencia-em-saude-publica-por-conta-da-covid-19-no-brasil. Accessed: 27 May 2025. May 2022 (cit. on pp. 28, 35).

[51] Brazilian Institute of Geography and Statistics (IBGE). *GDP Falls 4.1% in 2020 and Closes the Year at R$ 7.4 Trillion*. https://agenciadenoticias.ibge.gov.br/agencia-noticias/2012-agencia-de-noticias/noticias/30167-pib-cai-4-1-em-2020-e-fecha-o-ano-em-r-7-4-trilhoes. Accessed: 03 Mar 2021. Mar. 2021 (cit. on p. 28).

[52] Correio do Povo. *Emergency Aid Paid R$ 293.1 Billion to Nearly 68 Million in 2020, Says Caixa*. https://www.correiodopovo.com.br/not%C3%ADcias/economia/aux%C3%ADlio-emergencial-pagou-r-293-1-bilh%C3%B5es-a-quase-68-milh%C3%B5es-em-2020-diz-caixa-1.588541. Mar. 2021 (cit. on p. 28).

[53] Central Bank of Brazil. *Inflation Report: September 2020*. 2020 (cit. on p. 28).

[54] Jornal do Comércio. *E-commerce Revenue Grows 122% up to November*. https://www.jornaldocomercio.com/_conteudo/cadernos/jc_logistica/2020/12/772427-faturamento-do-e-commerce-cresce-122-ate-novembro.html. Porto Alegre, JC Logistics Section. Accessed: 26 May 2025. Jan. 2021 (cit. on p. 28).

[55] ABECS – Brazilian Association of Credit and Services Card Companies. *Card Payments Reach R$ 2 Trillion in 2020, an 8.2% Increase*. https://www.abecs.org.br/. Press Release. Feb. 2021 (cit. on pp. 28, 29).

[56] Mastercard. *Global Outlook 2021 Highlights Permanent Shift to Digital and Opportunity to Boost Financial Inclusion.* https://www.mastercard.com/news/eemea/en/newsroom/press-releases/en/2021/january/mastercard-global-outlook-2021-highlights-permanent-shift-to-digital-and-opportunity-to-boost-financial-inclusion-in-the-middle-east-and-africa/. Accessed: 20 May 2025. Jan. 2021 (cit. on p. 29).

[57] J. I. Heresi. "Credit Card Interchange Fees Revisited: The Role of Credit and Consumer Behavior". In: *International Journal of Industrial Organization* (2024). Forthcoming. Available at SSRN: https://ssrn.com/abstract=4917386 (cit. on p. 30).

[58] Marcos Ribeiro. *Fee Charged for the Use of 'Card Machines' Rises Again After Six Years of Decline.* Valor Investe. Accessed: 20 May 2025, Available at: https://valorinveste.globo.com/produtos/servicos-financeiros/noticia/2023/01/11/taxa-cobrada-pelo-uso-das-maquininhas-volta-a-subir-apos-seis-anos-de-queda.ghtml. Jan. 2023 (cit. on pp. 30, 31).

[59] Central Bank of Brazil. *Time Series Management System – SGS.* https://www3.bcb.gov.br/sgspub/localizarseries/localizarSeries.do?method=prepararTelaLocalizarSeries. Accessed: 1 June 2025. 2025 (cit. on pp. 31, 35, 36).

[60] Damodar N. Gujarati and Dawn C. Porter. *Basic Econometrics.* 5th. Porto Alegre: AMGH, 2011 (cit. on p. 35).

[61] Whitney K. Newey and Kenneth D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix". In: *Econometrica* 55.3 (1987), pp. 703–708 (cit. on p. 37).