

POLITECNICO
MILANO 1863

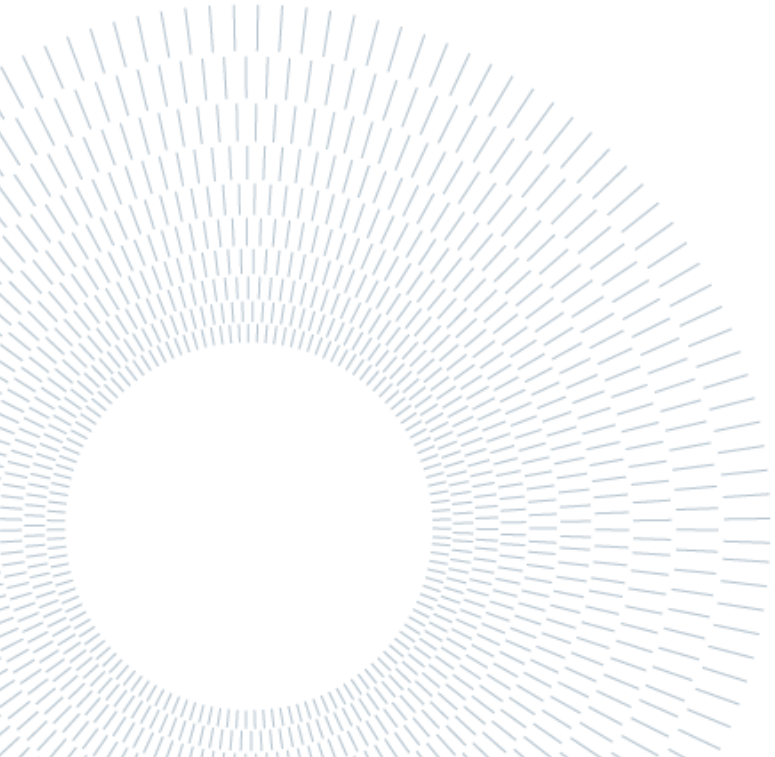
SCUOLA DI INGEGNERIA INDUSTRIALE
E DELL'INFORMAZIONE

Pix and Merchant Pricing: Competitive Pressure in Brazil's Card-Acquiring Market

TESI DI LAUREA MAGISTRALE IN
MANAGEMENT ENGINEERING
INGEGNERIA GESTIONALE

Author: Pedro Dias Hack

Student ID: 11068710
Advisor: Prof. Alessandro Perego
Co-advisor: Enrico Parenti, Veronica Anselmi
Academic Year: 2025-26



Abstract

This thesis examines whether the expansion of Pix changed merchant discount rates (MDR) in Brazil's card-acquiring market. Pix introduced a widely accessible and interoperable account-to-account payment infrastructure, offering merchants an alternative to card-based acceptance. Its rapid adoption could therefore increase competitive pressure on acquirers and reduce card acceptance costs, particularly for debit transactions.

The analysis combines quarterly payment, MDR, macroeconomic, and regulatory data in a staged interrupted time-series framework. It first evaluates changes in payment composition and then estimates debit and credit MDR models incorporating pre-existing trends, regulatory interventions, seasonality, macroeconomic controls, and lagged pricing persistence. Differenced, nonlinear, logarithmic, interaction, and alternative-exposure specifications are used to assess robustness.

The results confirm that Pix transformed the Brazilian payment system but do not identify a robust reduction in average card MDR attributable to its expansion. Negative Pix-related associations appear in some models, but they weaken or reverse once MDR persistence, earlier regulatory changes, and alternative specifications are considered.

The findings indicate that Pix expanded merchant choice and plausibly strengthened contestability, but these changes did not produce clearly identifiable pass-through into average card acceptance prices during the period studied. Competitive responses may instead have occurred through merchant-specific pricing, bargaining, service bundling, settlement conditions, or other dimensions not captured by aggregate MDR.

Key-words: Pix; merchant discount rate; acquiring; instant payments; competition dynamics; interrupted time series; Brazil.

Abstract in italiano

Questo studio esamina se l'espansione di Pix abbia modificato i tassi di sconto per i commercianti (MDR) nel mercato del *card-acquiring* in Brasile. Come alternativa di pagamento *account-to-account* ad ampia adozione, Pix avrebbe potuto aumentare la pressione competitiva sugli *acquirer*, riducendo i costi di accettazione delle carte, specialmente di debito.

L'analisi utilizza un modello a serie temporali interrotte (*staged interrupted time-series*) combinando dati trimestrali di mercato, macroeconomici e normativi. Vengono stimati i modelli MDR per debito e credito controllando per tendenze preesistenti, stagionalità, normative e persistenza dei prezzi, applicando diversi controlli di robustezza.

I risultati confermano il forte impatto di Pix sul sistema brasiliano, ma non identificano una riduzione robusta dell'MDR medio delle carte imputabile alla sua espansione. Gli effetti negativi riscontrati in alcuni modelli svaniscono se si considerano la persistenza dei prezzi e i precedenti interventi normativi.

In conclusione, Pix ha ampliato la scelta dei commercianti e la contestabilità del mercato, ma senza un chiaro *pass-through* sui prezzi medi di accettazione. La risposta competitiva potrebbe essersi manifestata su dimensioni non catturate dall'MDR aggregato, quali prezzi personalizzati, pacchetti di servizi o condizioni di liquidazione.

Parole chiave: Pix; merchant discount rate (MDR); acquiring; pagamenti istantanei; dinamiche competitive; serie temporali interrotte; Brasile.

Contents

Abstract ..... **iii**

Abstract in italiano ..... **v**

Contents **6**

1 Introduction **11**

1.1. Context 11

1.2. Motivation 13

1.3. Research Question and Scope of Inference 14

1.4. Contribution and Relevance 14

1.5. Structure of the Thesis 15

2 Literature Review **17**

2.1. Introduction 17

2.2. Real-Time Payments and Instant Payment Systems 18

2.3. Pix and the Transformation of Retail Payments in Brazil 21

2.4. Card Payments and Merchant Pricing 24

2.5. Competition and Concentration in the Brazilian Payments Market 27

2.6. Synthesis and empirical propositions 31

3 Methodology **33**

3.1. Introduction and methodological positioning 33

3.2. Data sources and sample construction 34

3.3. Variable construction 35

3.3.1. Merchant discount rates 36

3.3.2. Pix adoption and payment intensity 36

3.3.3. Intervention and timing variables 37

3.3.4. Control variables 38

3.4. Identification strategy 38

3.5. Exploratory analysis 39

3.6. Payment-composition models 41

3.7. Merchant discount rate models 41

3.7.1. Stage 1: segmented interrupted time-series model 42
3.7.2. Stage 2: dynamic interrupted time-series model 42
3.7.3. Stage 3: differenced robustness models 43
3.7.4. Functional-form extensions 44
3.8. Estimation, diagnostics, and model selection 45
3.9. Robustness and sensitivity checks 46
3.10. Reproducibility and auditability 47
3.11. Limitations of the methodology 47
3.12. Conclusion 49
4 Exploratory Analysis 51
4.1. Data coverage and descriptive overview 51
4.2. Pix adoption over time 54
4.3. Evolution of payment values and shares 57
4.4. Evolution of MDR before and after Pix 60
4.5. Pre/post-Pix descriptive comparison 63
4.6. Seasonality, stationarity, and preliminary diagnostics 65
4.7. Exploratory takeaways 68
5 Results 69
5.1. Overview of the empirical results 69
5.2. Payment-composition results 70
5.2.1. Pix share and debit share 70
5.2.2. Pix share and credit share 71
5.2.3. Alternative measures of payment composition 72
5.3. Baseline segmented interrupted time-series results 74
5.3.1. Debit MDR baseline model 74
5.3.2. Debit baseline model with Pix exposure 75
5.3.3. Credit MDR baseline model 77
5.3.4. Credit baseline model with Pix exposure 78
5.3.5. What the baseline stage establishes 79
5.4. Dynamic ITS results: preferred specifications 80
5.4.1. Why persistence changes the interpretation 80
5.4.2. Preferred debit MDR model 80
5.4.3. Dynamic debit model with exposure 82
5.4.4. Preferred credit MDR model 83
5.4.5. Dynamic credit model with exposure 85

5.4.6. Debit versus credit in the preferred models 86
5.5. Robustness analysis 87
5.5.1. Differenced models 87
5.5.2. Nonlinear trends 91
5.5.3. Logarithmic models 93
5.5.4. Exposure interactions 95
5.5.5. Alternative Pix proxies for debit MDR 98
5.6. Interpretation of control variables and institutional effects 98
5.6.1. The 2018 debit interchange cap 98
5.6.2. Covid 99
5.6.3. Selic and inflation 100
5.6.4. Seasonality 100
5.7. Diagnostic and model-selection assessment 100
5.8. Main empirical findings 102
6 Discussion and Interpretation 105
6.1. Answering the research question 105
6.2. Interpreting the central empirical result 106
6.2.1. Payment transformation did not imply price pass-through 106
6.2.2. Why the absence of a robust negative coefficient is informative 107
6.3. Debit and credit: expected and observed asymmetry 107
6.3.1. Why a stronger debit effect was expected 107
6.3.2. Why a robust debit response is not identified 108
6.3.3. Why credit MDR is more resilient 108
6.4. Interpreting the competitive mechanisms 109
6.4.1. Transaction substitution 109
6.4.2. Merchant bargaining and incumbent adaptation 109
6.4.3. Reduced dependence and coexistence 110
6.5. Pix in the evolution of Brazilian acquiring 111
6.5.1. Institutional sequencing 111
6.5.2. The 2018 interchange cap versus Pix 111
6.5.3. Pix as a distinct competitive shock 111
6.6. Pix and the European payment ecosystem 112
6.7. Contribution to the literature 115
6.8. Managerial implications 116
6.9. Policy implications 117

6.10. Limits of interpretation 118
6.10.1. Aggregation and measurement 118
6.10.2. Identification and overlapping events 118
6.10.3. Time horizon and outcome coverage 118
6.10.4. Model uncertainty 119
6.11. Discussion summary 119
7 Conclusion 121
7.1. Summary of the thesis 121
7.2. Main contribution 123
7.3. Final answer to the research question 124
7.4. Limitations 125
7.5. Future research 125
Bibliography 128
List of Figures 132
List of Tables 133
Acknowledgments 135

1 Introduction

1.1. Context

Retail payments have become a central component of economic infrastructure. Over the last two decades, the expansion of banking access, mobile connectivity, digital identification, and application-based financial services has shifted a growing share of transactions away from cash and toward electronic instruments. Payment systems consequently do more than execute transfers: their design affects transaction costs, liquidity, market access, data generation, financial inclusion, and the distribution of bargaining power across consumers, merchants, intermediaries, and infrastructure providers.

Fast payment systems are an important part of this transformation. They allow payment messages to be transmitted and final funds to become available to recipients in real time or near real time, generally on a continuous basis. Their significance extends beyond speed. When fast payments are interoperable, broadly accessible, and integrated into merchant and consumer interfaces, they can reduce coordination and settlement frictions and provide a common infrastructure on which additional services can be built (Committee on Payments and Market Infrastructures, 2021; Bank for International Settlements, 2024).

Brazil provides one of the most meaningful examples. Pix entered full operation in November 2020 as a publicly coordinated instant-payment infrastructure created by the Banco Central do Brasil (BCB). The BCB defined the rules, operated the central settlement infrastructure, required the participation of large institutions, and promoted common technical and user-experience standards. Mandatory participation and the central bank's combined role as infrastructure provider and rule-setter helped overcome the network-coordination problem that often constrains new payment systems (Banco Central do Brasil, 2023; Duarte et al., 2022).

Pix subsequently achieved nationwide scale. It supports person-to-person, person-to-business, business-to-business, and government-related transactions through banking and payment-institution interfaces. Its rapid growth demonstrates that a public payment infrastructure can become operationally relevant to consumers, firms, and incumbent financial institutions within a short period. The scale of

adoption also makes Pix economically relevant to markets that had previously depended on other payment rails, including the card-acceptance market.

The Brazilian card market had itself undergone substantial change before Pix. The acquiring sector was historically concentrated and shaped by links among major banks, card schemes, and acquirers. Antitrust and regulatory interventions gradually reduced scheme-acquirer exclusivity and facilitated entry by new acquirers and sub-acquirers. Competition intensified through merchant pricing, terminal distribution, settlement services, and product bundling. The 2018 debit interchange cap then directly changed an important component of debit-card acceptance costs (Conselho Administrativo de Defesa Econômica, 2017; de Castro et al., 2023). Pix therefore entered a market that was already evolving rather than a static pre-intervention environment.

One of the clearest observable prices in this market is the merchant discount rate (MDR), the percentage of card transaction value retained to compensate the acquiring, scheme, and issuing sides of the card ecosystem. MDR is economically important because it is a direct merchant-facing cost of card acceptance and a source of revenue within acquiring and related merchant services. It is not, however, a simple processing price. Card networks operate as two-sided markets in which prices and incentives are allocated across cardholders and merchants, and merchant fees can remain above narrow processing cost because they support cardholder benefits, network participation, risk management, financing, and other services (McAndrews & Wang, 2012; Rochet & Tirole, 2006; Wang, 2010).

Pix changes the merchant's set of alternatives. It enables immediate account-to-account settlement outside the traditional card chain and can involve lower direct acceptance costs. This creates two related competitive mechanisms. First, some transactions may migrate from cards to Pix, reducing the volume over which incumbent providers earn card-related revenues. Second, even without one-for-one substitution, Pix may improve merchants' outside option and bargaining position. Acquirers may respond through MDR, settlement conditions, terminal pricing, selective discounts, software, credit, or bundled services. The existence of a lower-cost rail therefore makes competitive pressure plausible, but it does not imply that average national MDR must fall mechanically.

The distinction between debit and credit is central. Pix is functionally closer to debit because both generally use funds already available to the payer. Credit cards additionally provide financing, instalments, rewards, consumer protections, and liquidity management. These features can preserve demand for credit-card acceptance even when a less expensive payment rail is available. A credible empirical analysis must therefore estimate debit and credit MDR separately rather than assume a uniform card-market response.

Pix may also complement rather than simply replace incumbent financial services. Evidence from Brazil indicates that Pix increased account activity and broader use of banking products, illustrating that payment technologies can expand digital participation while substituting for particular transactions (Sampaio & Ornelas, 2024). The relevant question is consequently not whether Pix eliminated cards, but whether its expansion changed the pricing dynamics of card acceptance after accounting for the market, regulatory, and macroeconomic forces operating at the same time.

1.2. Motivation

The thesis is motivated by a gap between the scale of Pix's transformation and the limited evidence on its effect on incumbent merchant pricing. Public and industry narratives frequently characterize Pix as disruptive because it is fast, interoperable, and generally inexpensive. Those characteristics make fee compression economically plausible, especially for debit. They do not establish that compression occurred. Prices may adjust slowly, card products may remain differentiated, and competition may operate through merchant-specific contracts or non-MDR dimensions that are not visible in an aggregate rate.

This distinction matters academically. Research on fast payments has concentrated on adoption, inclusion, technical design, and the use of banking services. Research on card pricing has developed a substantial account of two-sided markets, interchange, merchant acceptance, and regulation. Less work connects these literatures by testing whether the diffusion of a public instant-payment infrastructure is associated with changes in the merchant price of an incumbent private payment system.

The question is also managerially important. Acquirers, issuers, banks, fintechs, and merchant-service providers must determine whether Pix primarily reallocates transactions, changes merchants' negotiating leverage, or shifts competition toward broader service bundles. These mechanisms have different implications for pricing strategy, investment, and business-model adaptation. A fall in average MDR would indicate visible price pass-through. Stable aggregate MDR could instead coexist with selective discounts, faster settlement, lower equipment charges, or greater reliance on software and financial services.

The policy motivation is equally strong. Central banks and governments increasingly view payment infrastructure as a means of promoting efficiency, inclusion, resilience, interoperability, and competition. Brazil is frequently cited as evidence that a publicly coordinated system can overcome network effects and diffuse rapidly (Duarte et al., 2022). Whether that infrastructure also disciplines

incumbent merchant pricing is a more demanding test. It requires distinguishing the creation of a competitive alternative from measurable pass-through into the average price of card acceptance.

1.3. Research Question and Scope of Inference

The central research question is:

Has the expansion of Pix affected merchant discount rates in the Brazilian acquiring market?

The question is intentionally broad, but the empirical answer is bounded by the available identification strategy. Pix was launched nationally, so there is no contemporaneous untreated Brazilian market against which to compare the observed MDR path. The thesis therefore does not promise definitive causal identification. It evaluates whether MDR exhibits changes in level or trend after the Pix launch that remain statistically and economically coherent after accounting for pre-existing trends, lagged pricing persistence, macroeconomic conditions, the Covid-19 period, seasonality, and interchange regulation.

Two subsidiary questions organize the analysis:

1. Is the relationship between Pix expansion and MDR different for debit and credit transactions?
2. Are the timing, direction, and robustness of the estimated MDR changes consistent with increased competitive pressure from Pix?

The wording of the second question is important. A negative and robust post-Pix change would be consistent with competitive pressure, but the observational design could not prove that Pix alone caused it. Conversely, a statistically weak coefficient would not establish that Pix had no competitive effect. Aggregate MDR may conceal heterogeneous contracts, and competitive responses may occur through prices or services not observed in the public data. Throughout the thesis, the preferred interpretation is therefore whether the data identify a robust aggregate pricing association and whether that association is consistent with the proposed mechanism.

1.4. Contribution and Relevance

The thesis makes four contributions. First, it links the literature on public fast-payment infrastructure to the merchant-pricing literature. Pix is treated not only as an adopted technology but as a possible competitive constraint on the card-acquiring ecosystem.

Second, it separates payment-system transformation from identified transaction substitution. Pix, debit, and credit shares use a common denominator, and total Pix value includes transfers and other non-merchant uses. The analysis therefore uses payment-composition models descriptively and does not interpret their coefficients as one-for-one displacement of card purchases.

Third, it evaluates MDR through a staged time-series design. Transparent segmented interrupted time-series models are followed by dynamic specifications, differenced models, alternative trends, logarithmic outcomes, interaction models, and alternative Pix proxies. This progression shows which results survive a more credible treatment of persistence, non-stationarity, functional form, and collinearity.

Fourth, it distinguishes Pix from the institutional changes that preceded and overlapped it. In particular, the 2018 debit interchange cap and the revised 2023 debit and prepaid interchange regime are modeled separately. This distinction prevents the entire decline in debit MDR from being assigned to a post-2020 narrative and allows direct regulation to be compared with infrastructure-based competition.

The resulting contribution identifies what is strongly supported, what is descriptive, and what remains unresolved. Pix adoption and the transformation of aggregate payment composition are directly observable. Direct card substitution is not identified by common-denominator shares. The effect of Pix on average MDR must be judged by the stability of the intervention coefficients across model structures and diagnostics.

1.5. Structure of the Thesis

Chapter 2 develops the conceptual pathway from fast-payment infrastructure to merchant pricing. It reviews Pix's institutional design, card-platform economics, MDR formation, and the competitive history of the Brazilian acquiring market, and it derives the empirical propositions tested later. Chapter 3 presents the data, variable construction, identification strategy, model sequence, diagnostics, and limitations. Chapter 4 establishes the descriptive facts concerning data coverage, Pix adoption, payment composition, MDR trajectories, event-window comparisons, and time-series properties. Chapter 5 reports the econometric results and evaluates which findings survive diagnostic and robustness scrutiny. Chapter 6 interprets those findings in relation to the proposed mechanisms, theory, management, and policy. Chapter 7 provides the final answer, contributions, limitations, and research agenda

2 Literature Review

2.1. Introduction

The rapid transformation of retail payment systems in recent years has generated an expanding body of academic and institutional research examining the economic, technological, and regulatory implications of new payment infrastructures. Among these developments, the emergence of real-time payment systems, and particularly the introduction of Pix in Brazil, has attracted increasing attention from both scholars and policymakers. Existing literature has largely focused on the diffusion of these systems, their role in financial inclusion, and their impact on consumer payment behavior. However, less attention has been given to their potential effects on the pricing dynamics of incumbent payment instruments.

This literature review builds the conceptual chain required by empirical analysis. It begins with fast-payment infrastructure, then examines Pix's institutional design, card-platform pricing, and the competitive evolution of Brazilian acquiring. The objective is not to catalogue payment innovations, but to identify the mechanisms and confounding factors that determine whether Pix could affect merchant discount rates.

The central premise is that Pix may influence more than payment choice. Card systems connect issuers, acquirers, schemes, merchants, and consumers through a multi-sided pricing structure, so a new payment rail may affect incumbent behavior through transaction migration, merchant bargaining, or strategic adaptation (Armstrong, 2006; Evans & Schmalensee, 2007). MDR provides the principal observable merchant-facing price through which this possibility is evaluated.

Section 2.2 examines fast-payment systems as infrastructure and explains why interoperability, access, governance, and merchant integration determine their competitive relevance. Section 2.3 applies those insights to Pix and distinguishes rapid adoption from direct card substitution. Section 2.4 develops the economics of card acceptance, MDR, interchange, and debit-credit differentiation. Section 2.5 places the proposed mechanism in the Brazilian acquiring market, where competition and interchange regulation preceded Pix. Section 2.6 then converts the literature into the empirical propositions tested in the thesis.

2.2. Real-Time Payments and Instant Payment Systems

The emergence of real-time payment systems (RTP), also described as fast or instant payment systems, is a major development in modern payments. These systems transmit payment messages and make final funds available to the beneficiary in real time or near real time, commonly on a continuous basis. Their defining features are therefore not only speed but also availability, finality, and the capacity to support interoperable retail services (Committee on Payments and Market Infrastructures, 2021; Bank for International Settlements, 2024).

Although the operational feature most often associated with instant payments is speed, their economic relevance goes beyond faster transaction execution. In practice, RTP systems reduce several forms of friction that historically characterized retail payments. They can lower settlement delays, improve liquidity for households and businesses, reduce uncertainty regarding fund availability, and enable payment use cases that were previously less efficient or more costly under older systems. For merchants, in particular, immediate settlement may improve cash flow and reduce reliance on working-capital solutions tied to delayed receivables. For consumers, instant availability and broad accessibility can make digital payments more usable in day-to-day transactions. From a systemic perspective, fast payments can increase the efficiency and resilience of the payment ecosystem by offering an alternative to both cash-based and card-based instruments in a range of distinct transactional contexts. This is one reason why international organizations increasingly treat instant payment systems not simply as financial products, but as critical infrastructure for digital economies.

A key distinction is that between payment products and payment infrastructure. Visible instruments such as cards, wallets, applications, and QR interfaces rely on deeper systems governing initiation, messaging, clearing, settlement, access, and interoperability. Fast-payment systems operate at this infrastructural layer and may support overlay services such as aliases, request-to-pay, QR initiation, and account verification. Their economic effect consequently depends on governance, accessibility, interoperability, and merchant integration rather than settlement speed alone (Committee on Payments and Market Infrastructures, 2021).

Earlier research and policy analysis recognized that near-real-time retail infrastructure could intensify competition where incumbent systems depended on costly intermediation, network control, or high merchant switching frictions.

Historically, many retail payment markets have been dominated by card-based infrastructures, which involve multiple intermediaries (issuers, acquirers,

networks, processors, and merchants) and generate revenues through a combination of merchant fees, interchange arrangements, network charges, and value-added services. Instant payments differ from these arrangements in a crucial manner: they are typically based on account-to-account transfers, which can bypass or reduce some of the intermediation layers essential in card transactions. This means that, in certain payment contexts, instant payments may represent not just a new payment method, but a lower-cost alternative for merchant acceptance. Their competitive significance therefore depends not only on whether consumers use them, but also on whether merchants and payment service providers can integrate them into retail transactions in a way that is commercially viable and scalable.

The merchant side is central to the competitive significance of fast payments. A system can become a constraint on card acceptance only when it is operationally usable at the point of interaction, economically attractive to merchants, and sufficiently widespread among payers. QR standards, e-commerce integration, request-to-pay, and interoperable interfaces therefore determine whether fast payments remain primarily transfer instruments or become credible merchant-payment alternatives (Bank for International Settlements, 2024).

The relationship between instant payments and incumbent instruments should not be reduced to one-for-one substitution. Network effects, compatibility, and functional differentiation allow payment instruments to coexist even when they overlap in selected use cases (Katz & Shapiro, 1985). Consumers may retain credit cards for installments, rewards, or protections while using fast payments for transfers and immediate purchases. Merchants may likewise accept both instruments for different commercial reasons.

A payment system does not need to fully displace an incumbent model in order to alter market outcomes. It is sufficient for it to become a credible option in enough use cases to impact incumbent pricing and strategic behavior. In the context of merchant payments, this means that even partial migration toward instant payments can matter if it reduces merchants' dependence on card-based acceptance. The possibility that merchants can steer transactions toward a lower-cost alternative, or credibly threaten to do so, can place downward pressure on the fees sustained by incumbent providers. Recent BIS work on fast payments explicitly notes that easy, cheap, and instantaneous transfers can increase competition by lowering switching barriers and substituting more profitable payment methods, thereby potentially reducing margins in established payment businesses.

This logic is especially compelling in markets where the payment market has historically been characterized by high merchant dependence on cards and relatively expensive acceptance costs. In such environments, the introduction of a low-cost instant payment alternative may have stronger competitive implications

than in systems where merchant-side card pricing was already low or where instant payments remained confined to peer-to-peer use. This helps explain why instant payments have attracted growing interest not only from payment engineers and central banks, but also from scholars of market structure, competition, and financial intermediation. The question is no longer simply whether faster payments are technologically feasible or consumer-friendly, it is how deeply they can influence the economics of retail payments.

Another major dimension of the RTP literature concerns the role of public authorities and central banks. Fast payment systems can emerge through different institutional arrangements: they may be developed and operated by private groups, by public authorities, or through hybrid models. This institutional variation matters because it affects governance, access conditions, pricing, and the extent to which the system is oriented toward public policy objectives rather than shareholder returns. BIS analyses emphasize that central-bank involvement can be particularly important in overcoming coordination failures, solving early network-effect problems, and ensuring broad participation and interoperability.

This institutional dimension is crucial for understanding why some instant payment systems become transformative while others remain uncompetitive. Adoption and impact depend not only on the existence of fast settlement, but also on a broader set of design choices: whether participation is widespread, whether the system is easy to integrate into user interfaces and merchant workflows, whether the pricing structure encourages use, whether the system supports point-of-sale and e-commerce use cases, and whether trust in the system is sufficiently high. In other words, instant payment systems are not homogeneous. Their competitive effects vary according to their design, governance, and integration into the broader financial and commercial ecosystem. This makes cross-country comparisons useful but also reinforces the need to examine specific cases on their own set of particularities.

From the perspective of this thesis, the broader RTP literature is important because it suggests that instant payment systems can, under certain conditions, become infrastructural substitutes or competitive constraints on legacy payment systems. It also clarifies that such effects are likely to be strongest where instant payments are widely accessible, low-cost, interoperable, and sufficiently integrated into merchant use cases. These insights are particularly relevant for the Brazilian case, where Pix was introduced not simply as a transfer product, but as a national payment infrastructure with broad reach and rapid merchant adoption.

Instant payment systems can reduce transaction frictions, improve merchant economics, and alter decision-making in retail payments, therefore, their expansion

may affect not only payment behavior, but also the pricing equilibrium of incumbent payment systems.

2.3. Pix and the Transformation of Retail Payments in Brazil

The introduction of Pix in November 2020 is one of the most consequential recent developments in retail payments. The Brazilian case stands out for the pace and scale of adoption and for the BCB's role as system designer, operator, regulator, and catalyst (Banco Central do Brasil, 2023; Duarte et al., 2022).

Pix is an instant account-to-account payment system created within the institutional framework of the BCB. It operates continuously and supports initiation through keys, QR codes, and account information across personal, business, and government use cases (Banco Central do Brasil, 2023).

One of the defining features of Pix is that it was created not as a single payment product, but as a deep public payment infrastructure. This distinction matters because it helps explain why Pix achieved an impact that many private payment innovations failed to achieve. Rather than entering the market as a case-specific solution, Pix was implemented as an interoperable infrastructure layer that could be accessed through a broad range of financial institutions and user interfaces. The Central Bank did not simply regulate the system externally, it actively designed its rules, defined its architecture, and operated the underlying settlement process, called the “Sistema de Pagamentos Instantâneos” (SPI). This institutional deployment gave Pix a sense of universality and neutrality that other private payment schemes lack. This public-infrastructure orientation also means that Pix was built with explicit policy goals, including efficiency, competition, innovation, and financial inclusion, rather than solely around the profit-maximizing logic of private payment schemes.

Pix scaled rapidly across individuals and firms and became one of Brazil's most frequently used payment instruments. This outcome reflects broad participation and the availability of multiple use cases from launch rather than evidence of a single substitution channel (Banco Central do Brasil, n.d.).

The literature attributes Pix's rapid diffusion to institutional design, broad participation, low user costs, interoperability, and integration into existing financial applications. Mandatory participation by large institutions helped resolve the cold-start problem, while the BCB's combined infrastructure and rule-setting roles established common standards and trust (Duarte et al., 2022).

Pricing reinforced these adoption mechanisms. Pix is generally free for individuals, and merchant charges are often lower than card acceptance costs. Low direct cost strengthens Pix as a merchant alternative, although a cost comparison alone does not establish equivalent functionality or automatic pass-through into MDR (Duarte et al., 2022).

A further reason for Pix's impact lies in the fact that it was not restricted to a single transactional niche. Unlike some instant payment systems that initially remain confined to peer-to-peer transfers, Pix was deliberately designed to support a wide range of retail payment use cases from the beginning. These include not only person-to-person and person-to-business transfers, but also e-commerce transactions, tax and bill payments, government collections, scheduled transfers, cash withdrawals through merchants and ATMs, and, increasingly, recurring and programmable payment functionalities. The range of these use cases matters because it increases the number of transactional contexts in which Pix can plausibly substitute for or compete with existing payment methods. This multifunctionality is one of the reasons why Pix is more analytically relevant than many narrower payment innovations.

For merchants, in particular, Pix introduced a potentially meaningful change in the economics of payment acceptance. Merchant transactions in Brazil had long been strongly mediated by card-based infrastructures, especially in face-to-face retail and small business contexts. Pix created an alternative payment route in which merchants could receive funds immediately, often at lower cost, and without relying on deep layers of intermediation. This matters because merchant payment acceptance is not simply a matter of operational convenience, it is closely associated with cash flow, cost management, pricing decisions, and strategic platform independence. A payment method that settles instantly and carries lower acceptance costs may be attractive to merchants not only because it improves margins, but also because it reduces the need to wait for settlement or rely on receivable-based working capital solutions. The possibility that merchants can encourage consumers toward Pix may, therefore, have implications beyond immediate per-transaction costs.

This merchant-side dimension is crucial to understand because it links Pix directly to the question of Merchant Discount Rates (MDR) and competitive pressure in the acquiring market. The key issue is not simply whether Pix fully replaced card transactions, but whether its expansion made merchants less dependent on card-based acceptance and therefore more resistant to the fee structures sustained by incumbent payment systems. In payment markets, a new instrument does not need to fully dominate usage in order to affect incumbent pricing. It may be enough for it to become sufficiently widespread and credible in merchant-relevant contexts to

alter the bargaining power and constrain the pricing dynamics of existing intermediaries. This is especially plausible in a market like Brazil's, where card acceptance costs historically mattered more for small and medium merchants and where acquirer monetization has long depended on merchant-side fees and related services.

At the same time, even though Pix is launched with extremely diverse use-case employments, its effects should not be analyzed as uniform across all payment functions. One of the most important distinctions in the literature and in market practice is between debit-like payment functions and credit-based payment functions. Pix is structurally closer to debit because it is based on the immediate transfer of existing account balances. It does not, at least in its original form, replicate the embedded financing, installment functionality, and consumer liquidity smoothing associated with credit cards. This means that the competitive implications of Pix are likely to be heterogeneous across the debit to credit landscape. It may act as a more direct substitute for debit card transactions and for certain low-ticket or immediate-payment merchant contexts, while generating a weaker or more indirect effect on credit card usage and pricing. This distinction is crucial to help explain why the literature on Pix cannot be reduced to a single question of "adoption" or "replacement." The more relevant issue is how Pix interacts with different segments of the incumbent payment ecosystem and whether those interactions translate into different forms of pricing pressure.

Pix also has broader implications for financial inclusion and digital participation. Sampaio and Ornelas (2024) find that Pix increased active banking relationships and the use of additional financial services. This evidence demonstrates that payment technologies can complement parts of the banking system while substituting for particular transactions.

Despite the growing literature on Pix, most existing studies and policy discussions have focused on its adoption, usage patterns, inclusion effects, technical design, and security implications. While these are important areas of inquiry, they do not fully address one of the most important economic questions raised by Pix: whether its expansion altered the pricing power of incumbent payment infrastructures. In particular, there remains relatively limited systematic analysis of whether Pix generated measurable pressure on merchant-facing card fees, especially after accounting for the fact that the Brazilian acquiring market was already undergoing changes before Pix was introduced. This gap is particularly relevant because the merchant side is where the economics of payment acceptance, competitive pressure, and platform monetization become most visible.

Taken together, the literature suggests that Pix occupies a unique position at the intersection of payment innovation, public infrastructure, and market competition.

It is not simply an example of instant payments in practice, but a powerful case through which to examine how new payment systems may influence the economics of incumbent solutions.

2.4. Card Payments and Merchant Pricing

To understand why the emergence of Pix may matter for merchant-facing prices in Brazil, it is first necessary to examine the economic structure of the card payment system it may be impacting. Card payments remain one of the most important forms of retail electronic payment worldwide, particularly in merchant transactions, and their pricing architecture has been one of the most debated topics in the economics of payment systems. Unlike simple account-to-account transfers, card transactions are embedded in a multi-layered network of institutions and fees, in which pricing outcomes reflect not only operational costs, but also strategic interactions between market players in the payments ecosystem. For this reason, the merchant-facing cost of accepting cards, commonly observed through the Merchant Discount Rate (MDR), cannot be interpreted as a purely technical fee. Rather, it is the result of a broader economic structure that allocates costs, incentives, and bargaining power across the payment ecosystem. The literature on payment cards has long emphasized that the economics of card acceptance are shaped by the institutional design of the network itself, and not simply by transactional processing costs.

Card payment systems typically operate through a four-party model, involving the cardholder, the merchant, the issuer (the financial institution providing the card to the consumer), and the acquirer (the institution enabling the merchant to accept card payments). These actors are linked through a card network or scheme, such as Visa or Mastercard, which sets technical and commercial rules governing transaction routing, authorization, clearing, and settlement. In a typical transaction, the merchant receives the purchase value minus a fee charged by the acquirer, while the issuer receives compensation through the interchange mechanism, and the network receives its own assessment or scheme fees. This means that what appears to the merchant as a single fee is, in reality, the outcome of a complex pricing mechanism involving multiple institutions and relationships. This complexity is one of the reasons why merchant fees in card markets have attracted sustained attention from both scholars and regulators.

Within this system, the Merchant Discount Rate (MDR) is especially important because it is the most visible and economically meaningful price faced by merchants for accepting card payments. MDR is generally defined as the percentage of the transaction value retained by the acquiring side when a merchant accepts a card

payment. Although terminology can vary across different markets, MDR usually incorporates at least three main components: the interchange fee, which compensates the issuer, the scheme or network fee, charged by the card network, and the acquirer's own margin, which covers processing, merchant servicing, distribution, risk management, and profit. In practice, MDR acts as a merchant-side summary price for access to the card network. This is why MDR is particularly relevant for the present thesis: if Pix has altered the competitive conditions of merchant payments in Brazil, it is sure to impact the Merchant Discount Rate in a observable manner.

The fact that MDR is observable does not make it straightforward to interpret. Card platforms must attract both cardholders and merchants, so their price structure reflects cross-side network effects and the allocation of incentives across the platform. Merchant-facing fees can therefore remain above narrow processing costs when they support cardholder adoption, rewards, and usage (McAndrews & Wang, 2012; Rochet & Tirole, 2006; Wang, 2010; Wright, 2003).

Lower processing costs do not necessarily pass through one-for-one when platform pricing and market structure allow margins or cross-subsidies to persist. Interchange allocates revenue between the acquiring and issuing sides and is commonly incorporated into MDR. It therefore affects merchant pricing while also supporting cardholder-side incentives (Rochet & Tirole, 2011; Wang, 2010).

For example, Ardizzi et al. (2018), in the Italian context, show that the capping of interchange fees contributed to a sizeable reduction in merchant fees and increased card acceptance at the point of sale. Similarly, more recent work on the Brazilian debit card market by de Castro et al. (2023) finds that the 2018 cap on domestic debit interchange fees was associated with lower debit MDR, while also illustrating that card pricing outcomes depend on interactions between interchange, scheme fees, and issuer/acquirer strategies. These findings show that merchant fees are sensitive not only to demand-side conditions, but also to the institutional and regulatory structure of the payment network. In other words, MDR is not purely determined by market dynamics, it is also shaped by rules, governance, and regulation in the payments structure.

Beyond interchange, the merchant-facing cost of cards is also influenced by the role of the acquirer, which is especially important in the Brazilian context. Acquirers do more than simply "process" transactions. They act as the commercial interface between the merchant and the card ecosystem, offering payment acceptance services, terminal infrastructure, fraud management, settlement services, merchant onboarding, and often additional financial or software products. In many markets, especially those with strong SME participation, acquirers also monetize merchants through POS rental, service bundling, software integrations, and most importantly,

receivables anticipation or discounting. This means that the economic significance of MDR goes beyond its percentage value as a transaction fee. It is embedded in a broader merchant monetization strategy in which payment acceptance can serve as an anchor for a wider commercial relationship. Aurazo (2024), in his study of interchange, access pricing, and sub-acquiring, shows that merchant pricing in card ecosystems cannot be understood without accounting for the layered role of intermediaries and the way competition unfolds across direct acquirers, sub-acquirers, and merchant-facing service providers. This is highly relevant for Brazil, where the merchant acceptance market evolved not only through card processing competition, but through the development of a broader merchant services industry.

This broader merchant service logic is also what makes merchant dependence such an important concept. For many merchants, especially small and medium-sized businesses, accepting cards is not simply an operational option, it is often a commercial necessity. Consumers increasingly expect card acceptance, and in many sectors refusing cards may imply a direct loss of sales. This gives acquirers and card schemes an important position in the transaction chain, especially when alternative payment methods are limited or less usable. Historically, one of the reasons merchant fees remained relatively resilient in many markets is precisely that merchants often had weak alternatives. Even if they considered acceptance costs high, refusing cards was not a realistic commercial strategy.

An additional reason why card pricing must be treated carefully is that debit and credit card transactions are economically distinct products, even when both appear to merchants as "card payments." From the perspective of merchant pricing and substitution, this distinction is fundamental. Debit card payments are generally closer to immediate payment functions, given that the transaction draws directly from the consumer's deposit balance and settlement occurs with limited financing. Credit card payments, however, typically bundle the payment function with a financing function, allowing consumers to defer payment and, in some countries such as Brazil, to split purchases into installments. This means that credit cards provide a broader economic service than pure execution. As a result, the merchant fees associated with credit transactions often reflect not only payment processing, but also the costs associated with consumer credit.

This distinction matters directly for the relationship between cards and instant payments. RTP systems such as Pix are much closer to debit-like payment functions than to credit. They provide immediacy of transfer but not necessarily financing or credit. For this reason, the competitive pressure generated by Pix on card pricing should not be considered to be uniform across all card transactions. If Pix generates downward pressure on MDR, one should expect that pressure to be more relevant

where cards are used primarily as a payment instrument rather than as a financing instrument.

The literature also highlights that merchant pricing is often heterogeneous across merchant types, which further complicates how MDR should be interpreted. Smaller merchants typically face less bargaining power, lower transaction volumes, and less favorable contractual conditions than larger retail chains, which can negotiate lower effective acceptance costs. Studies of merchant fee incidence often find that market structure and merchant size matter substantially for card acceptance. In practice, this means that average MDR may hide important nuances across different merchant segments. The literature strongly suggests that any competitive pressure generated by alternative payment systems may be especially relevant for the segment of merchants historically facing higher fees. This is particularly important in the Brazilian case, where much of the commercial battle in acquiring over the last decade was centered on small and medium merchants, especially through the distribution of POS devices and bundled services.

In general, the literature on card payments suggests that merchant pricing emerges from a complex combination of platform economics, fee allocation, intermediary structure, and merchant dependence. MDR is therefore best understood not simply as a technical processing cost, but as a merchant-facing cost of the card ecosystem as a whole. This is an important conclusion because it reinforces why MDR is a meaningful variable to study competitive change in payment markets and it shows why the rise of Pix is important: if Pix offers merchants a cheaper and more immediate, then it may place pressure on one of the core merchant monetization mechanisms of the incumbent card ecosystem.

2.5. Competition and Concentration in the Brazilian Payments Market

Brazil represents a highly relevant setting for studying the interaction between new payment infrastructures and incumbent pricing structures because its retail payments market combines several important features: historically strong reliance on electronic card payments, a previously concentrated acquiring sector, a sequence of regulatory interventions aimed at increasing competition, and, more recently, the relevant expansion of a state-coordinated instant payment system. This combination makes the Brazilian market especially useful for examining whether a new payment system such as Pix can alter the competition dynamics in merchant payments and, ultimately, the pricing behavior of incumbent systems.

For much of the 2000s and early 2010s, the Brazilian acquiring market was characterized by a high degree of concentration and strong associations between

major banks, card schemes, and merchant acquirers. The sector was largely dominated by a small number of vertically connected players, most notably Cielo and Rede, which were historically associated with the country's largest banking groups. This structure gave rise to a payment acceptance environment in which merchant access to card networks was heavily mediated by a small number of dominant firms. In practice, this meant that merchants often had little effective choice over how to access certain card brands or under what commercial conditions. These structural features are important because they help explain why merchant-facing fees in Brazil remained a persistent issue in both market and regulatory discussions for many years. The Brazilian acquiring market did not emerge as a naturally decentralized ecosystem, it evolved through a historically concentrated architecture in which access to major schemes was decisive.

One defining feature of the earlier Brazilian market was scheme-acquirer exclusivity. CADE agreements in 2017 targeted arrangements involving major schemes and acquirers because they restricted rival access and increased merchant costs. The intervention is relevant because it documents merchant-pricing concerns and pro-competitive reform before Pix (Conselho Administrativo de Defesa Econômica, 2017).

The dismantling of exclusivity was one of the most important milestones in the competitive opening of the Brazilian acquiring market because it reduced one of the main institutional barriers that protected incumbent acquirers and helped create the conditions for a more contested merchant acceptance environment. This change also contributed to the spread of interoperable POS devices and to the broader entry of new merchant acquirers and sub-acquirers. This gave rise to a more dynamic market in which firms competed not only through scheme access, but also through pricing, terminal deployment, settlement speed, merchant support, and bundled services. It is within this context that Brazil experienced what became popularly known as the "maquininha war" a period of intensified rivalry in the merchant acquiring segment marked by aggressive expansion strategies, fee competition, and the rapid rise of new entrants targeting small and medium-sized businesses. This earlier wave of competition is essential to understanding the later impact of Pix, because it implies that any observed change in merchant pricing after 2020 cannot be interpreted as emerging from a static or previously unreformed market.

This point is especially important because one of the central challenges of this study is distinguishing the possible effect of Pix from the broader transformation already underway in the Brazilian payments ecosystem. The literature and regulatory record make clear that the market had already been moving toward greater openness and rivalry prior to the introduction of instant payments. New acquirers, fintechs, and merchant-focused payment institutions had begun to challenge

incumbent firms, especially in the SME segment. The acquisition of GetNet by Santander, for example, reflected the strategic importance of acquiring as a competitive battleground among major financial institutions. Over time, the Brazilian merchant payments market evolved from a highly bank-centered and concentrated structure into a more fragmented environment, even if significant asymmetries remained.

In addition to the end of exclusivity, another major regulatory development with direct relevance for merchant pricing was the 2018 cap on domestic debit card interchange fees introduced by the Central Bank of Brazil. This measure is particularly important because it directly affected one of the key components of MDR and therefore had a measurable impact on merchant-side pricing even before Pix. The empirical study by de Castro, Schmitz, and Azevedo (2023) shows that the interchange cap led to a statistically significant and gradual reduction in debit MDR in the quarters following its implementation. The study also finds that the effect was concentrated in the debit segment and did not spill over in the same way to credit cards, reinforcing the importance of the distinction between the credit and debit markets. Any attempt to identify a "Pix effect" must therefore control for the fact that part of the observed fee compression in the debit segment may reflect earlier regulatory intervention rather than competition from instant payments alone.

Brazilian law also permits price differentiation by payment instrument, increasing merchants' formal capacity to steer consumers toward methods with lower acceptance costs (Brazil, 2017). Steering does not guarantee migration, but it can make a lower-cost outside option more commercially relevant.

These developments suggest that the Brazilian payments market had already become significantly more competitive and open before Pix was launched. However, this does not imply that merchant-side pricing had become fully competitive or that the market concentration ended fully. Even with new entrants and more pro-competitive regulatory reforms, incumbent firms continue to benefit from scale, installed merchant relationships, bank affiliations, and control over complementary financial services. Even after the entry of challengers and regulatory interventions, merchant dependence on card acceptance remained high, especially in sectors where electronic payment acceptance had become indispensable. In this sense, the Brazilian market prior to Pix can be understood as one in which competition had increased, but where incumbent card-based infrastructures still retained great strategic importance.

This is precisely why the introduction of Pix may have represented a qualitatively different kind of shock. Unlike previous competitive changes in the acquiring market, which largely involved rivalry within the same card-based ecosystem, Pix introduced a structurally distinct option that was not simply another acquirer,

another POS provider, or another merchant service brand. Instead, it created a distinct account-to-account payment infrastructure with a fundamentally different intermediation and cost structure. From the perspective of merchant competition, this is crucial. Earlier changes in the acquiring market may have intensified rivalry among firms offering access to the same underlying card mechanism, but Pix changed the merchant's options altogether by creating a non-card alternative that was instant and low-cost. This makes Pix distinct from earlier waves of acquiring competition and suggests that its effects are different from within-system rivalry.

The Brazilian context also makes this especially plausible because Pix entered a market in which electronic payments were already deeply embedded in everyday commercial life. Brazil was not a case where instant payments needed to create digital payment habits from scratch. Rather, Pix was introduced into an environment in which consumers and merchants were already accustomed to electronic transactions, smartphone-based banking, and digital interfaces. This matters because the barrier to replacing or complementing existing payment instruments is much lower when users are already digitally integrated into the payment system. A new payment system can scale not by building trust from zero, but by redirecting existing economic behavior through a more efficient or lower-cost option. This may help explain why Pix moved beyond peer-to-peer transfers relatively quickly and became commercially relevant in a short period of time.

From the standpoint of merchant-side competition, at least four mechanisms appear especially relevant in the Brazilian case.

The first is transaction substitution. Some transactions that would previously have been executed through debit cards, "boleto", or even credit may have migrated toward Pix once it became accepted and convenient. This is the most direct channel through which Pix could affect card-based pricing: if a meaningful share of merchant transactions moves away from cards, the transaction base over which acquirers and card networks extract revenue becomes less secure.

The second mechanism is merchant bargaining power. Even if full substitution remains limited, the presence of Pix may still improve the merchant's outside option in a way that affects pricing power. Merchants that can credibly threaten to move customers toward Pix, especially in face-to-face retail, or low-ticket environments, may become less dependent to card acceptance. This matters even if aggregate card usage remains high, because pricing power in payments often depends on dependence rather than on absolute volume alone.

The third mechanism is strategic adaptation by incumbents. Acquirers, issuers, and merchant service providers may respond to Pix not only by competing on transaction fees, but also by redesigning product bundles, accelerating settlement,

lowering MDR selectively, or shifting their monetization toward software, embedded finance, and merchant ecosystem services. In this sense, Pix may influence pricing even indirectly, by changing the strategic posture of incumbent firms rather than directly displacing their volume. This is consistent with broader literature on contestable platform markets, in which the presence of a credible alternative often affects pricing behavior before market shares shift measurably.

The fourth mechanism is heterogeneous exposure across payment functions and merchant segments. Pix is more substitutable for debit-like payment functions than for credit card functions involving installment finance or liquidity providing. Therefore, smaller merchants, who historically faced higher fees and greater sensitivity to working capital timing, may be more exposed to the economic advantages of Pix than larger merchants with stronger bargaining power and more resilient financial processes. These asymmetries are especially relevant in Brazil because the SME segment has long been central to the economics of the acquiring industry and to the commercial expansion strategies of merchant acquirers.

The key analytical point is that the significance of Pix does not depend solely on whether it became widely used, but on whether its expansion reduced merchants' dependence on incumbent card-based systems in a way that influenced pricing power. Brazil offers a rich environment to examine whether a publicly coordinated instant payment alternative can alter the competitive conditions of merchant payments in a historically concentrated market.

2.6. Synthesis and empirical propositions

Literature supports a plausible mechanism but does not imply a predetermined empirical result. Fast-payment infrastructure can increase contestability when it is interoperable, inexpensive, broadly adopted, and usable by merchants. Pix satisfies these conditions. Card-pricing theory, however, shows that lower infrastructure cost need not pass directly into MDR because card systems provide differentiated services and allocate prices across two sides of a platform.

The first proposition is therefore descriptive: Pix should become a large component of the payment system and measured card shares should decline relative to the expanded denominator. This evidence establishes system transformation but cannot identify direct substitution because Pix includes non-merchant transactions and the shares are mechanically related.

The second proposition concerns debit MDR. Because Pix is closest to an immediate account-funded payment, sustained competitive pass-through would appear as a negative post-Pix change in debit MDR after accounting for the pre-existing trend, persistence, macroeconomic conditions, Covid-19, seasonality, and interchange

regulation. A negative coefficient in an uncontrolled or diagnostically weak model is insufficient.

The third proposition is that any Pix-related pricing response should be weaker for credit than for debit because credit combines payment with financing, installments, rewards, and protections. This is an expected asymmetry rather than an identifying assumption; the data may fail to demonstrate it if neither card function exhibits robust compression.

The fourth proposition concerns direct regulation. If interchange is an input into merchant acceptance cost, the 2018 debit interchange cap should have a negative and more debit-specific relationship with MDR. Distinguishing this policy from Pix is necessary because the regulation preceded the launch and debit MDR was already declining.

These propositions determine the empirical sequence. Chapter 4 first establishes adoption, composition, and pricing trajectories. Chapter 5 then evaluates whether the expected MDR patterns survive dynamic correction, alternative functional forms, different Pix proxies, and formal diagnostics.

3 Methodology

3.1. Introduction and methodological positioning

This chapter presents the empirical strategy used to examine whether the expansion of Pix affected merchant discount rates in the Brazilian acquiring market. The methodological design follows directly from the research question developed in the previous chapters: whether the rapid diffusion of a publicly coordinated instant payment infrastructure changed the pricing dynamics of incumbent card-based payment systems, and whether this effect differs between debit and credit transactions.

The empirical challenge is that Pix was not introduced as a local pilot, a staggered reform, or a treatment applied only to a subset of firms or regions. It was launched nationally in November 2020 and rapidly became available across the Brazilian financial system. This institutional feature is central to the methodological choice of the thesis. Because virtually the entire Brazilian payments market was exposed to Pix at the same time, the analysis cannot rely on a conventional treated-versus-untreated comparison within Brazil. Instead, the empirical design exploits temporal variation: the evolution of payment composition and card-pricing variables before and after the introduction and diffusion of Pix.

For this reason, the methodology is best characterized as an applied quantitative time-series study with a intervention structure. The central framework is an interrupted time-series (ITS) design adapted to gradual adoption. This approach is appropriate when an intervention has a known start date and affects a single aggregate system over time, but when there is no credible untreated control group. In this thesis, the interruption is the introduction of Pix in 2020Q4; however, the expected impact is not modelled only as an immediate break. Pix adoption was progressive, and its possible effects on merchant pricing were likely mediated by merchant acceptance, consumer usage, incumbent strategic responses, and contractual adjustment frictions. The methodology therefore combines segmented ITS models with dynamic specifications, differenced robustness checks, and alternative Pix-intensity proxies.

The empirical analysis is built around two linked channels. The first is a payment-composition channel: Pix may have changed the relative use of payment

instruments, particularly debit and credit cards. The second is a merchant-pricing channel: Pix may have affected merchant discount rates by reducing merchant dependence on card-based acceptance or by increasing competitive pressure on acquirers. The methodology is therefore structured to first document the evolution of Pix adoption and payment shares and then estimate whether the post-Pix period is associated with changes in MDR behavior after controlling for relevant macroeconomic and institutional factors.

The chapter proceeds from measurement to identification and then to robustness. Section 3.2 describes the data and sample construction, while Section 3.3 defines the outcomes, exposure measures, interventions, and controls. Section 3.4 explains why a national interrupted time-series design is appropriate and where its identifying limits remain. Section 3.5 defines the exploratory checks that validate the setting. Sections 3.6 and 3.7 present the payment-composition and MDR model sequences. Sections 3.8 and 3.9 establish the diagnostic, model-selection, and sensitivity protocol. Section 3.10 documents reproducibility, Section 3.11 states the methodological limitations, and Section 3.12 links the design to the empirical chapters.

3.2. Data sources and sample construction

The empirical analysis is based primarily on publicly available data from the Banco Central do Brasil (BCB). The BCB data were used because they provide consistent aggregate information on Brazilian retail payment instruments, including Pix, card transactions, merchant discount rates, and interchange-related variables. These data are suitable for the purpose of the thesis because the research question concerns market-level pricing and substitution dynamics rather than the behavior of individual merchants, acquirers, or consumers.

The database was constructed as a quarterly master dataset in which each observation corresponds to one quarter of the Brazilian payments market. The quarterly frequency was chosen for both conceptual and practical reasons. Conceptually, merchant pricing in the acquiring market is unlikely to adjust instantaneously at a daily or weekly frequency; contractual conditions, fee schedules, regulatory changes, and strategic repricing typically evolve over longer intervals. Practically, the main dependent variables of interest, especially debit and credit MDR, are available and consistently interpretable at quarterly frequency. Aggregating all variables to a common quarterly structure avoids mixed-frequency estimation problems and ensures that Pix adoption, card transaction indicators, macroeconomic controls, and MDR outcomes are aligned in the same observational unit.

The construction of the master dataset followed six steps. First, raw payment datasets were imported and standardized. These included aggregate payment transaction data, credit and debit card transaction data, terminal-related information, merchant discount rate data, and interchange-related data. Second, variables originally reported at monthly frequency were transformed into quarterly values. Flow variables, such as transaction value and transaction count, were aggregated by summing monthly observations within each quarter. Rate variables, such as interest rates or inflation measures, were averaged or otherwise harmonized consistently over the quarter. Third, payment values and counts were separated by instrument, including Pix, debit cards, credit cards, and prepaid cards. Fourth, pricing indicators were aggregated by card function to produce debit MDR and credit MDR. Fifth, macroeconomic controls and policy/event variables were merged into the master dataset. Finally, validation checks were performed to identify missing observations, duplicate quarters, gaps in the time series, and implausible negative values in core financial variables.

Before aggregation, source units were normalized explicitly. In the BCB general-payments series used by the pipeline, Pix value is reported in millions of reais and Pix transaction count in thousands of transactions. The raw fields were therefore multiplied by 1,000,000 and 1,000, respectively, before quarterly totals, average ticket values, ratios, and payment shares were calculated. This correction aligns the dataset with the official Pix statistics and prevents scale errors from propagating through the empirical measures (Banco Central do Brasil, n.d.).

The resulting dataset is designed to support both descriptive and econometric analysis. It contains the main pricing outcomes, payment-volume indicators, Pix adoption measures, payment-share variables, macroeconomic controls, seasonal indicators, and intervention variables. The use of a single quarterly master dataset also improves reproducibility: each graph, table, and model in the empirical chapters is derived from the same canonical data structure.

3.3. Variable construction

The empirical design requires variables that capture two different dimensions of market change: pricing outcomes and payment-system composition. The main dependent variables are merchant discount rates for debit and credit card transactions. The main explanatory variables capture Pix adoption, Pix intensity relative to card transactions, institutional timing, macroeconomic conditions, and seasonal effects.

3.3.1. Merchant discount rates

The primary pricing outcomes are debit MDR and credit MDR. MDR represents the merchant-facing fee charged for accepting card payments and is therefore the most direct observable indicator of merchant-side pricing in the card-acquiring ecosystem. Because the thesis examines whether Pix created competitive pressure on incumbent card payment systems, MDR is the central outcome variable.

Separate models are estimated for debit MDR and credit MDR. This separation is theoretically necessary. Pix is structurally closer to debit-like payment functions because it transfers existing funds in real time and does not, in its original form, provide consumer credit, installment financing, or reward-based intertemporal substitution. Credit card transactions, by contrast, often combine payment execution with financing and installment functions, especially in Brazil. Therefore, if Pix generates competitive pressure on card pricing, the effect is expected to be more direct for debit MDR than for credit MDR.

When MDR observations are available at a more disaggregated level within the source structure, quarterly weighted averages are computed by card function. Let m_{itk} denote the MDR observation for unit i in quarter t and card function k, where k represents debit or credit. Let w_{itk} denote the corresponding transaction-weight variable. The weighted average MDR is defined as:

$$\bar{M}_t^k = \frac{\sum_i m_{itk}\, w_{itk}}{\sum_i w_{itk}} \tag{1}$$

This procedure ensures that the quarterly MDR reflects the relative importance of underlying transaction volumes rather than giving equal weight to observations with different market relevance.

3.3.2. Pix adoption and payment intensity

Pix adoption is measured through transaction value and transaction count. Let P_t denote Pix transaction value in quarter t, D_t debit card transaction value, C_t credit card transaction value, and PP_t prepaid card transaction value. Total payment value is defined as:

$$TV_t = P_t + D_t + C_t + PP_t \tag{2}$$

From this aggregate, payment-share variables are constructed:

$$\begin{aligned} s_t^{Pix} &= \frac{P_t}{TV_t}, \\ s_t^{Debit} &= \frac{D_t}{TV_t}, \\ s_t^{Credit} &= \frac{C_t}{TV_t}. \end{aligned} \tag{3}$$

These shares are used to examine whether Pix expansion coincided with changes in the composition of electronic retail payments. The Pix share captures the penetration of Pix in the total payment mix, while debit and credit shares capture the relative position of the incumbent card instruments.

A second Pix variable is constructed to capture the intensity of Pix relative to debit card transactions:

$$r_t^{Pix/Debit} = \frac{P_t}{D_t} \tag{4}$$

This ratio is especially relevant because Pix is expected to be a closer substitute for debit than for credit. A higher Pix-to-debit ratio indicates that Pix has become large relative to the debit card transaction base, which may increase the competitive pressure faced by debit card acquirers. Additional Pix proxies, such as log Pix value, Pix share, and Pix-to-card ratios, are used in robustness checks to verify whether the results depend on a specific measurement choice.

3.3.3. Intervention and timing variables

The empirical models include deterministic intervention variables that encode the timing of Pix. A linear time trend is defined as:

$$TIME_t = t, \qquad t = 1,2, \dots, T \tag{5}$$

The Pix intervention indicator is defined as:

$$POST_t = \begin{cases} 0, & t < 2020Q4, \\ 1, & t \geq 2020Q4. \end{cases} \tag{6}$$

where 2020Q4 is the quarter in which Pix was launched. To capture gradual post-launch diffusion, a post-intervention time variable is also constructed:

$$TA_t = \begin{cases} 0, & t < t_0, \\ TIME_t - TIME_{t_0} + 1, & t \geq t_0. \end{cases} \tag{7}$$

This variable allows the model to estimate whether the trajectory of MDR changed after Pix was introduced, rather than treating the intervention only as an immediate one-time level shift. This is important because the economic effects of Pix were likely cumulative: adoption, merchant acceptance, consumer familiarity, and incumbent responses developed progressively after launch.

3.3.4. Control variables

The models include a set of controls intended to reduce the risk that the estimated Pix-related coefficients capture unrelated macroeconomic, seasonal, or regulatory effects. Macroeconomic controls include the Selic rate and inflation. When available, the real Selic rate is also considered, defined as the difference between the nominal Selic and inflation. These variables are relevant because interest rates and inflation may affect financial-sector pricing, consumer behavior, merchant financing costs, and the broader economic environment in which payment choices are made.

The models also include event and policy controls. The Covid-period dummy equals one from 2020Q1 through 2022Q2, covering the principal disruption to retail activity and payment behavior in the estimation window. Two regulatory indicators separate Pix from interchange-policy changes: debit_cap_dummy begins in 2018Q4, when the initial debit interchange limits entered into force, and tic_cap_dummy begins in 2023Q2, when the revised debit and prepaid interchange regime became effective. These controls are necessary because interchange is a direct component of card acceptance costs and the 2018 cap was explicitly expected to reduce debit MDR (Banco Central do Brasil, 2018, 2022).

Finally, quarterly seasonal dummies are included to account for recurring within-year patterns. Q4 is omitted as the baseline quarter, while Q1, Q2, and Q3 are included in the regression specifications. Seasonality is relevant because payment volumes, merchant activity, consumer spending, and retail composition may vary systematically across quarters.

3.4. Identification strategy

The main identification problem is that Pix was introduced nationally and simultaneously. This makes it difficult to apply methods such as difference-in-differences in a conventional way, because there is no obvious untreated Brazilian market that can serve as a control group. Similarly, panel pass-through models at the acquirer or merchant level would require disaggregated data that are not available in the public BCB datasets used in this thesis.

Given these constraints, the identification strategy relies on an interrupted time-series framework. ITS models compare the level and trajectory of an outcome before

and after a known intervention while controlling for pre-existing trends and observable confounders. In this thesis, the intervention is not interpreted only as the legal launch of Pix, but as the beginning of a new payment-infrastructure regime whose effect may grow over time. The ITS framework is therefore adapted to gradual diffusion through the inclusion of both a post-Pix indicator and a time-after-Pix variable.

The baseline interpretation is as follows. The pre-Pix time trend captures the underlying trajectory of MDR before the introduction of Pix. The post-Pix indicator captures any immediate level shift associated with the intervention quarter. The time-after-Pix variable captures whether the slope of MDR changed after Pix began operating. In exposure-augmented models, Pix intensity variables capture whether MDR is associated with the scale of Pix adoption, conditional on the general post-intervention structure.

This design does not eliminate all threats to causal inference. Other events occurred around the same period, including the Covid-19 shock, changes in macroeconomic conditions, and ongoing regulatory and competitive developments in the payments market. The methodology addresses these threats through controls, dynamic specifications, diagnostic testing, and robustness checks. However, the results should still be interpreted with appropriate caution. The objective is not to claim perfect causal identification, but to assess whether the observed evolution of MDR is consistent with Pix-related competitive pressure after accounting for major observable confounders.

This bounded causal language is important. The empirical strategy can support statements such as “Pix expansion is associated with a change in MDR dynamics” or “the evidence is consistent with competitive pressure generated by Pix.” It cannot, by itself, prove that Pix was the only cause of MDR changes. The contribution of the thesis lies in the disciplined evaluation of this relationship using the best available aggregate public data and a transparent, reproducible time-series framework.

3.5. Exploratory analysis

Before estimating the econometric models, the thesis conducts an exploratory analysis of the full quarterly dataset. This step is not merely descriptive; it is part of the empirical validation process. In time-series analysis, visual inspection and descriptive statistics are essential for understanding trend behavior, event timing, seasonality, outliers, and possible structural breaks.

The exploratory analysis begins with line charts of payment values and payment shares by method. These figures document the evolution of Pix, debit cards, credit

cards, and prepaid cards over time. Event markers are added for major institutional moments, including the debit interchange cap, the Covid period, the Pix launch, and later tariff-cap changes when relevant. These markers allow visual comparison between payment dynamics and institutional shocks.

The second part of the exploratory analysis focuses on Pix adoption. Pix transaction value, transaction count, Pix share, Pix-to-debit ratio, and related growth indicators are plotted over time. This makes it possible to verify whether Pix adoption was gradual, whether its growth coincided with changes in card-payment shares, and whether the magnitude of Pix became large enough to plausibly affect incumbent pricing.

The third part examines MDR behavior. Debit MDR and credit MDR are plotted separately, with rolling averages and event markers. The credit-minus-debit MDR spread is also examined to assess whether the two card functions evolved differently after Pix. This distinction is important because the theoretical expectation is not that Pix affects debit and credit equally. A visible divergence between debit and credit MDR dynamics would support the decision to estimate separate models.

The exploratory stage also includes descriptive statistics, pre/post comparisons, correlation matrices, seasonality summaries, and stationarity tests. Pre/post comparisons are used to document whether average MDR, payment shares, and Pix-intensity measures differ between the periods before and after Pix. Correlation matrices are interpreted cautiously because trending variables can generate misleading raw correlations. Seasonality checks help determine whether quarter dummies should be retained in the econometric models. Stationarity tests, including Augmented Dickey-Fuller and KPSS tests where applicable, help assess whether level regressions should be complemented by dynamic or differenced specifications.

The purpose of this exploratory analysis is to ensure that the formal models are not estimated mechanically. Instead, the models are grounded in observable data behavior and institutional timing. If the descriptive evidence does not support the existence of meaningful Pix adoption, payment-composition changes, or post-Pix MDR movement, then any regression-based interpretation would be weaker. Conversely, if the exploratory analysis shows coherent patterns, the econometric models can be interpreted as a formal test of those patterns under controls and diagnostics.

3.6. Payment-composition models

The first econometric stage examines how Pix expansion is associated with changes in the measured composition of electronic payments. This is relevant to the competitive-pressure argument because Pix became a large alternative payment rail. However, the exercise is descriptive: it does not by itself identify how much card spending was economically displaced by Pix.

The substitution models use debit share and credit share as dependent variables. The baseline specification is shown in Equation (8).

$$y_t = \alpha + \beta_1 TIME_t + \beta_2 s_t^{Pix} + \boldsymbol{\gamma}'\mathbf{X}_t + \boldsymbol{\delta}'\mathbf{Q}_t + \epsilon_t, \quad y_t \in \{s_t^{Debit}, s_t^{Credit}\} \tag{8}$$

where y_t is either debit share or credit share, s_t^{pix} is the Pix share of total payment value, X_t is the vector of macroeconomic and event controls, and Q_t represents quarterly seasonal dummies.

The coefficient of interest is β_2. In the debit-share model, a negative β_2 indicates that higher Pix penetration coincides with a lower debit share of the constructed payment-value total. The analogous credit coefficient is interpreted in the same compositional sense. These signs are not treated as direct estimates of transaction substitution because credit cards also provide credit and installment functions that Pix does not replicate.

These payment-composition models are not intended to establish the final pricing effect of Pix or to identify causal substitution. Pix share, debit share, and credit share are constructed from the same total-payment denominator. An increase in the Pix numerator therefore lowers the measured card shares mechanically, even if card transaction values remain unchanged. The models are retained as descriptive evidence about the changing aggregate payment mix, estimated with heteroskedasticity- and autocorrelation-consistent standard errors and evaluated together with residual and collinearity diagnostics.

3.7. Merchant discount rate models

The core empirical analysis estimates the relationship between Pix and merchant discount rates. The modeling strategy is implemented as a staged ladder rather than a single specification. This is necessary because aggregate payment and pricing variables are persistent over time, and because a simple pre/post regression may confuse intervention effects with trend, autocorrelation, or omitted functional form. The staged approach allows the thesis to begin with a transparent segmented ITS

model and then progressively address the main statistical risks identified by diagnostics.

3.7.1. Stage 1: segmented interrupted time-series model

The first stage estimates a segmented ITS model in levels for debit MDR and credit MDR separately. For card function k, where k represents debit or credit, the baseline model is:

The ITS specification and model-selection logic follow established guidance that emphasizes explicit level and slope terms, attention to autocorrelation, sensitivity to functional form, and transparent comparison of candidate models (Linden, 2015; Lopez Bernal et al., 2018).

$$M_t^k = \alpha + \beta_1 TIME_t + \beta_2 POST_t + \beta_3 TA_t + \boldsymbol{\gamma}'\mathbf{X}_t + \boldsymbol{\delta}'\mathbf{Q}_t + u_t \quad (9)$$

In Equation (9), M_t^k is MDR for card function k, $TIME_t$ captures the secular pre-existing trend, $POST_t$ captures the immediate post-Pix level shift, TA_t captures the post-Pix slope change, X_t includes macroeconomic and policy controls, and Q_t includes seasonal dummies.

The interpretation of the ITS coefficients is straightforward. β_2 measures the immediate change in MDR at the start of the Pix period, conditional on controls. β_3 measures the change in the MDR trend after Pix. A negative and statistically meaningful β_3 for debit MDR would be consistent with the hypothesis that MDR began to decline more rapidly after Pix became available.

An exposure-augmented version of the model adds the Pix-to-debit ratio:

$$M_t^k = \alpha + \beta_1 TIME_t + \beta_2 POST_t + \beta_3 TA_t + \beta_4 r_t^{Pix/Debit} + \boldsymbol{\gamma}'\mathbf{X}_t + \boldsymbol{\delta}'\mathbf{Q}_t + u_t \quad (10)$$

This specification tests whether the intensity of Pix relative to debit card value is associated with MDR after controlling for intervention timing. It is especially relevant for debit MDR because the Pix-to-debit ratio directly captures the scale of Pix relative to the card function for which substitution is theoretically strongest.

3.7.2. Stage 2: dynamic interrupted time-series model

The second stage introduces a lagged dependent variable. This step was motivated by both statistical diagnostics and economic reasoning. Statistically, MDR series are persistent; if residual autocorrelation remains in a segmented ITS model, standard coefficient inference may be unreliable. Economically, merchant pricing does not adjust instantly. MDR reflects contractual relationships, acquiring strategies,

market competition, regulation, and merchant negotiations, all of which may generate inertia.

The dynamic ITS model is defined as:

$$M_t^k = \alpha + \rho M_{t-1}^k + \beta_1 TIME_t + \beta_2 POST_t + \beta_3 TA_t + \boldsymbol{\gamma}'\mathbf{X}_t + \boldsymbol{\delta}'\mathbf{Q}_t + u_t \quad (11)$$

The exposure-augmented version adds $r_t^{Pix/Debit}$ to the same structure. The coefficient ρ captures persistence in MDR. When rho is large, current MDR is strongly related to the previous quarter's MDR, and the intervention coefficients should be interpreted as incremental effects conditional on pricing inertia.

The dynamic ITS model is the preferred primary specification. Its estimand is conditional and short-run. $POST_{PIX}$ measures the current-quarter level displacement associated with entry into the post-Pix regime after controlling for the previous quarter's MDR and the remaining covariates. TIME_AFTER_PIX measures the incremental change in quarterly slope under the same conditioning set. Neither coefficient is an unconditional total effect of Pix. Long-run multipliers are not emphasized because persistence is high and the credit-lag confidence interval approaches or crosses unity, making long-run transformations unstable.

3.7.3. Stage 3: differenced robustness models

The third stage estimates differenced models as a robustness check. In these models, the dependent variable is the quarter-to-quarter change in MDR:

$$\Delta M_t^k = M_t^k - M_{t-1}^k \quad (12)$$

The core differenced specification is shown in Equation (13).

$$\Delta M_t^k = \theta_0 + \theta_1 \Delta TA_t + \boldsymbol{\eta}'\Delta\mathbf{X}_t + \boldsymbol{\delta}'\mathbf{Q}_t + \nu_t \quad (13)$$

The exposure version adds the change in the Pix-to-debit ratio:

$$\Delta M_t^k = \theta_0 + \theta_1 \Delta TA_t + \theta_2 \Delta r_t^{Pix/Debit} + \boldsymbol{\eta}'\Delta\mathbf{X}_t + \boldsymbol{\delta}'\mathbf{Q}_t + \nu_t \quad (14)$$

Differencing helps test whether the results are driven by trending level relationships. However, differenced models are not treated as the main economic interpretation because they remove much of the long-run level information that is central to the concept of merchant pricing pressure. Their role is to act as a stress test: if the direction of the Pix-related relationship remains similar in differences, confidence in the result increases; if it changes substantially, the level-based interpretation should be treated more cautiously.

3.7.4. Functional-form extensions

After the core three-stage ladder, additional functional-form checks are estimated to assess whether model fit and diagnostics improve without sacrificing interpretability. These include nonlinear trend specifications, log-outcome specifications, and interaction specifications.

The nonlinear dynamic model adds a quadratic time trend:

$$M_t^k = \alpha + \rho M_{t-1}^k + \beta_1 TIME_t + \beta_2 TIME_t^2 + \beta_3 POST_t + \beta_4 TA_t + \boldsymbol{\gamma}'\mathbf{X}_t + \boldsymbol{\delta}'\mathbf{Q}_t + u_t \quad (15)$$

This specification allows the underlying MDR trajectory to bend smoothly over time instead of assuming a strictly linear trend. It is useful when visual inspection or RESET tests suggest that a linear time trend may be too restrictive.

The log-outcome model estimates the dynamic ITS structure using the logarithm of MDR:

$$\ln\left(M_t^k\right) = \alpha + \rho M_{t-1}^k + \beta_1 TIME_t + \beta_2 POST_t + \beta_3 TA_t + \boldsymbol{\gamma}'\mathbf{X}_t + \boldsymbol{\delta}'\mathbf{Q}_t + u_t \quad (16)$$

This specification can stabilize variance and allows coefficients to be interpreted approximately in percentage terms. It is used as robustness rather than as the main specification because the thesis is primarily interested in MDR percentage-point changes, which are more directly interpretable in levels.

Finally, interaction models allow the effect of Pix intensity to vary after the intervention and over the post-Pix period:

$$M_t^k = \text{core dynamic terms} + \kappa_1\left(POST_t \times r_t^{Pix/Debit}\right) + \kappa_2\left(TA_t \times r_t^{Pix/Debit}\right) + u_t \quad (16)$$

These models test whether the marginal association between Pix intensity and MDR differs across regimes or grows over time. Because interaction terms can be difficult to interpret in a short aggregate time series and may be sensitive to collinearity, they are treated as exploratory robustness evidence rather than as the primary model for thesis conclusions.

3.8. Estimation, diagnostics, and model selection

All regression models are estimated by ordinary least squares. Because the data are time-series and residual autocorrelation is plausible, inference is based on heteroskedasticity- and autocorrelation-consistent covariance estimators, specifically Newey-West/HAC standard errors. This is a conservative choice that adjusts standard errors for serial correlation and heteroskedasticity in the residuals. Given the quarterly frequency and the limited sample size, the baseline implementation uses a parsimonious lag structure for the HAC correction.

Before estimation, each candidate model is subjected to data and design checks. Observations with missing or infinite values in required variables are dropped on a model-specific basis. Regressors with insufficient variation are excluded, and full-rank checks are used to avoid singular or unidentified model designs. This is important because Pix variables, time trends, post-intervention indicators, and macro controls may be highly correlated in a short time series. The objective is to ensure that each estimated equation is statistically identifiable and reproducible.

After estimation, each model is evaluated using a diagnostic protocol. Residual autocorrelation is examined using the Durbin-Watson statistic and the Breusch-Godfrey test. Heteroskedasticity is assessed through Breusch-Pagan and White tests. Functional-form adequacy is evaluated using RESET tests. Parameter stability is assessed using CUSUM-type tests. Residual normality is evaluated using the Jarque-Bera test, not as a strict requirement for validity under HAC inference, but as an additional indicator of residual behavior. Variance-inflation factors are used to assess multicollinearity among regressors.

For segmented ITS models, the post-intervention terms are also evaluated jointly when appropriate. This is important because the Pix effect may not appear only as an isolated immediate shift or only as a slope change. A joint test of POST and TIME_AFTER_PIX helps evaluate whether the post-Pix regime as a whole is statistically informative.

Model selection is not based exclusively on adjusted R-squared or statistical significance. Instead, the thesis uses a multi-criterion approach that balances fit, diagnostics, economic interpretability, and complexity. A model with slightly better fit but severe autocorrelation, unstable coefficients, or difficult-to-interpret interaction terms is not necessarily preferred. Conversely, a simpler model with acceptable diagnostics and clear economic interpretation may be more appropriate for the main thesis narrative.

This principle is especially relevant in the MDR analysis. The segmented level ITS model is transparent but may suffer from residual serial dependence. The dynamic

ITS model improves the treatment of persistence and therefore serves as the preferred primary specification. Differenced, nonlinear, log, and interaction models are used to evaluate the sensitivity of the main findings. The final interpretation prioritizes results that are directionally coherent across specifications, diagnostically acceptable, and consistent with the institutional logic of the Brazilian payment market.

3.9. Robustness and sensitivity checks

The robustness strategy addresses four main concerns: dependence on a specific Pix proxy, sensitivity to functional form, differences between debit and credit, and vulnerability to concurrent shocks.

First, the analysis varies the measurement of Pix exposure. Pix is represented alternatively by the post-Pix timing variable, log Pix transaction value, Pix share, and the Pix-to-debit ratio. Each proxy captures a different theoretical channel. The time-after-Pix variable captures gradual diffusion after launch. Log Pix value captures scale. Pix share captures penetration in the total payment mix. The Pix-to-debit ratio captures direct rivalry with the debit card transaction base. If the findings are consistent across these proxies, the interpretation that Pix affected card-market dynamics becomes stronger. If signs or significance change substantially, the results are treated as more fragile.

Second, the analysis estimates alternative functional forms. Nonlinear time trends test whether the MDR trajectory is better represented by smooth curvature than by a simple linear trend. Log models test whether the results depend on scale and variance assumptions. Interaction models test whether Pix intensity has different effects in the post-Pix period than before. These specifications are used to probe the stability of the main findings, not to maximize fit opportunistically.

Third, debit and credit MDR are always modeled separately. This is both a robustness decision and a theoretical requirement. Because Pix is closer to debit than to credit, similar results for debit and credit would require careful interpretation. A stronger debit-side response would be more consistent with the substitution and merchant-bargaining mechanism developed in the literature review.

Fourth, the models include controls for the Covid period, macroeconomic conditions, seasonality, the debit interchange cap effective from 2018Q4, and the revised debit and prepaid interchange regime effective from 2023Q2. These controls cannot eliminate all confounding risks, but they reduce the probability that the estimated Pix coefficients simply reflect major observable shocks or direct

regulatory changes. The results are therefore interpreted not as isolated proof of causality, but as evidence from a controlled time-series framework.

3.10. Reproducibility and auditability

The empirical workflow was implemented as a reproducible pipeline. The process begins with construction of the quarterly master dataset, continues through exploratory analysis, substitution modeling, MDR modeling, robustness tests, and final result export. Each stage produces tables, figures, diagnostic outputs, and intermediate workbooks. This structure allows the empirical results to be traced back to the underlying data transformations and model specifications.

Reproducibility is important for two reasons. First, the thesis relies on multiple linked transformations: monthly-to-quarterly aggregation, weighted MDR construction, share and ratio creation, event coding, macro-control merging, and model-specific sample selection. Without an auditable pipeline, it would be difficult to verify whether the final results are driven by the theoretical model or by hidden data-handling choices. Second, the staged modeling strategy generates many outputs. A reproducible workflow ensures that the selection of the preferred model is based on documented diagnostics and robustness evidence rather than informal judgment.

The methodology therefore treats the empirical pipeline itself as part of the research design. The canonical analysis is executed through code/00_run_pipeline.py in the repository-local Python environment. It constructs outputs/master_quarterly.csv and then writes tables to outputs/tables, intermediate workbooks to outputs/xlsx, diagnostic metadata to outputs/metadata, and figures to graphs. The final environment uses Python 3.12.10, pandas 3.0.0, NumPy 2.4.1, matplotlib 3.10.8, statsmodels 0.14.6, and openpyxl 3.1.5. The final data snapshot was regenerated in June 2026; no comparative analysis treats partial 2026Q2 Pix data as a completed quarter. The repository README provides the exact execution command and artifact map.

The repository developed for this thesis is open-source and publicly available on GitHub at https://github.com/hackpedro/polimi-masters-thesis.

3.11. Limitations of the methodology

The methodology has limitations that must be explicitly acknowledged. The first limitation is the use of aggregate data. Aggregate BCB statistics are appropriate for studying market-level dynamics, but they do not allow direct observation of merchant-level heterogeneity, acquirer-level pricing strategies, contract-level MDR

changes, or firm-specific responses to Pix. As a result, the thesis cannot determine whether particular types of merchants or acquirers experienced stronger Pix-related effects.

The second limitation is the absence of a conventional control group. Because Pix was introduced nationally, it is not possible to observe a comparable Brazilian payments market that was not exposed to Pix. The ITS framework addresses this by comparing pre- and post-intervention trajectories, but it remains vulnerable to overlapping shocks. The inclusion of controls and robustness checks mitigates this concern but does not fully eliminate it.

The third limitation is the finite post-intervention window. Although Pix adoption was rapid, structural pricing responses in acquiring markets may unfold over a longer horizon. The available post-Pix period may capture early and medium-term adjustments, but not necessarily the full long-run equilibrium effect of Pix on card pricing.

The fourth limitation concerns the economic comparability of the payment measures. Total Pix value includes person-to-person (P2P), person-to-business, business-to-business, bill, tax, and other transfers. The debit and credit series, by contrast, predominantly measure purchases made through card rails. The numerators therefore do not represent identical transaction universes. In particular, a P2P Pix transfer increases measured Pix value even though it is not a purchase that could normally have generated card MDR.

This distinction also qualifies the use of the terms Pix share, debit share, and credit share. In the dataset, these variables are constructed as each instrument's value divided by the combined value of Pix, credit, debit, and prepaid cards. They are descriptive shares of a deliberately broad payment-value denominator, not market shares in the strict industrial-organization sense of mutually substitutable products within a defined relevant market. When P2P or another non-merchant Pix flow raises the denominator, the measured card shares fall mechanically even if the absolute value of card purchases is unchanged. The share regressions therefore combine genuine changes in payment behavior with an accounting relationship.

The broad Pix measures were retained because the public quarterly series provides the longest consistent indicator of Pix scale and because system-wide adoption can still matter indirectly. P2P use expands familiarity, network reach, active accounts, and the installed user base from which merchant use can develop. Accordingly, pix_share, logged Pix value, and the Pix-to-debit ratio are used loosely as measures of system penetration or competitive exposure. They are not treated as measures of person-to-business volume, direct card displacement, or a merchant-level

substitution elasticity. The Pix-to-debit ratio changes the scaling of exposure but does not remove the non-merchant transactions from its numerator.

This measurement problem has two implications. First, interpreting the negative payment-share coefficients as one-for-one substitution would overstate the evidence because part of the relationship is mechanical and part of Pix value has no card equivalent. Second, using broad Pix value in the MDR models may dilute a true merchant-payment relationship because the exposure variable contains transactions that do not place direct pressure on acquiring revenue. The direction and magnitude of the resulting coefficient bias cannot be established from the aggregate series alone. More granular data separating person-to-business receipts from P2P and other transfers would be required to identify direct substitution and connect Pix exposure to merchant pricing more precisely.

These limitations define the scope of inference. The thesis does not claim to provide definitive causal proof that Pix alone reduced MDR. Instead, it tests whether the timing, direction, and robustness of the observed MDR dynamics are consistent with the hypothesis that Pix increased competitive pressure in the Brazilian acquiring market. Within the constraints of public aggregate data, the methodology provides a transparent and academically defensible framework for evaluating that hypothesis.

3.12. Conclusion

This chapter has presented the methodology used to analyze the relationship between Pix expansion, payment composition, and merchant discount rates in Brazil. The empirical design is grounded in the institutional reality of Pix: a nationwide, publicly coordinated payment infrastructure introduced in 2020Q4 and adopted progressively over time. Because this setting does not permit a standard untreated control group, the thesis relies on a time-series strategy centered on interrupted time-series models, dynamic specifications, and robustness checks.

The methodology first constructs a quarterly master dataset from BCB payment statistics and macroeconomic controls, with explicit conversion of Pix value and count fields into reais and transactions before aggregation. It then uses exploratory analysis to document Pix adoption, payment-share changes, and MDR evolution. Payment-composition models describe how the broad payment mix changed but are not interpreted as causal substitution estimates because the shares use a common denominator. The core MDR analysis estimates segmented and dynamic ITS models separately for debit and credit MDR, complemented by differenced, nonlinear, log, interaction, and alternative-exposure specifications.

This methodological structure is aligned with the research question while imposing explicit limits on inference. It recognizes that Pix may affect incumbent card systems through usage and pricing pressure, but it also separates those theoretical mechanisms from what can be identified with aggregate observational data. The next chapters apply the framework to the evidence and report whether the proposed competitive effect survives controls for persistence, macroeconomic conditions, Covid, seasonality, and interchange regulation.

4 Exploratory Analysis

This chapter examines the empirical setting before the formal econometric models are estimated. Its purpose is not to attribute a causal effect to Pix, but to establish the main features of the data that any credible model must explain. The analysis proceeds in four stages. First, it evaluates the coverage and internal consistency of the quarterly master dataset. Second, it documents the speed and scale of Pix adoption and the associated reweighting of aggregate payment values. Third, it describes the long-run evolution of debit and credit merchant discount rates (MDR), paying particular attention to whether the series display an obvious break around the launch of Pix. Finally, it evaluates pre/post differences, seasonality, persistence, and stationarity in order to motivate the dynamic and robustness specifications used in Chapter 5.

The exploratory evidence is especially important in this thesis because the Brazilian setting does not provide a conventional untreated control group. Pix was introduced nationally in November 2020 and rapidly became available throughout the financial system. Consequently, the empirical argument depends on a careful reading of time-series patterns and on separating three propositions that are related but not equivalent: Pix became economically important; the aggregate payment mix changed after its introduction; and card-acceptance prices changed because of Pix. The first two propositions can be assessed descriptively. The third requires the econometric controls and counterfactual structure developed in Chapter 3 and estimated in Chapter 5.

4.1. Data coverage and descriptive overview

The master dataset contains 86 quarterly observations from 2005Q1 to 2026Q2. This full calendar range is useful for maintaining a single canonical time index, but the effective sample differs across variables because the underlying Banco Central do Brasil series begin and end at different dates. Debit and credit MDR are observed from 2005Q1 through 2025Q4, providing 84 usable quarterly observations for the central pricing analysis. Debit and credit transaction values are available from 2011Q1 through 2026Q1, while prepaid-card value begins in 2016Q3. Pix value and

transaction count are represented throughout the master index, with structural zeros before the launch quarter and positive observations beginning in 2020Q4.

Table 4.1 - Coverage of the quarterly master dataset

Variable group	Coverage used/available	Observations	Exploratory treatment
Master quarterly index	2005Q1–2026Q2	86	Maintains the complete calendar
Debit and credit MDR	2005Q1–2025Q4	84	Pricing analysis ends in 2025Q4
Debit and credit values	2011Q1–2026Q1	61	Comparative figures end in 2025Q4
Prepaid-card value	2016Q3–2026Q1	39	Shown only where observed
Complete positive Pix quarters	2020Q4–2025Q4	21	Partial 2026Q2 excluded from figures
Macroeconomic controls	2005Q1–2026Q2	86	Aligned to the quarterly calendar

Note: The common comparison horizon ends in 2025Q4. The 2026Q2 Pix observation is partial and is excluded from comparative figures. Source: Author's construction from Banco Central do Brasil data.

The different end dates require a distinction between the master-data horizon and the horizon used in comparable charts. Card values are available for 2026Q1, but MDR ends in 2025Q4. The Pix observation for 2026Q2 contains only the months available at the time the source files were updated, through April 2026, and is therefore not a complete quarterly flow. Treating it as a full quarter would create an artificial collapse in Pix value and count. It would also produce a misleading Pix share of 100 per cent because the corresponding 2026Q2 card values are not yet observed. For this reason, all comparative figures in this chapter end in 2025Q4. The partial 2026Q2 observation remains in the underlying master dataset for transparency but is not used as evidence of a change in trend.

The data-quality checks identify no duplicated quarters, no missing periods within the master calendar, and no negative values in the core payment and MDR variables. The missing observations reported for card values and MDR arise from

source coverage rather than breaks within their respective series. This distinction matters because an unbalanced set of variable-specific starting dates is not equivalent to an interrupted time series. Where multiple instruments are compared, the chapter uses the common period for which the relevant variables are jointly available.

An additional validation concerned the units of the original Pix fields. In the BCB general-payments source used by the pipeline, Pix value is reported in millions of reais and Pix count in thousands of transactions. The construction procedure therefore multiplies the source value field by 1,000,000 and the count field by 1,000 before quarterly aggregation. This correction is economically consequential: without it, Pix values, average tickets, payment shares, and exposure ratios would be understated by several orders of magnitude. The resulting series were checked against the scale of official Pix statistics before being included in the master dataset.

The descriptive distributions are strongly affected by the timing of Pix. The median Pix value and count over the full 2011Q1–2025Q4 comparison period are zero because more than half of that interval precedes its launch. A full-period mean is therefore not a useful description of a technology that enters late and grows rapidly. The same issue affects Pix growth rates: percentage growth from a zero or very small initial base is undefined or extremely large. The chapter consequently emphasizes dated milestones, levels, shares, and ratios rather than relying on a single full-sample average or on early percentage-growth observations.

The MDR series have a different structure. Over 2011Q1–2025Q4, median credit MDR is approximately 2.49 per cent and median debit MDR approximately 1.41 per cent. Credit MDR is consistently higher than debit MDR, as expected given the additional financing, installment, fraud, and product features associated with credit transactions. Both series also exhibit substantial low-frequency movement: the difference between early-sample and late-sample observations is much larger than the typical quarter-to-quarter change. This smoothness anticipates the importance of persistence and trend controls in the formal models.

Table 4.2 - Descriptive statistics for principal variables

Variable	Period	Mean	Median	Std. Dev	Min.	Max.
Debit MDR (%)	2005Q1–2025Q4	1.415	1.527	0.200	1.081	1.609
Credit MDR (%)	2005Q1–2025Q4	2.619	2.754	0.299	2.054	2.993
Pix value (R$ tn)	2020Q4–2025Q4	4.528	3.900	2.967	0.150	10.215
Pix count (bn)	2020Q4–2025Q4	10.399	9.397	6.960	0.176	22.287
Credit value (R$ bn)	2011Q1–2025Q4	316.905	208.925	213.679	93.432	841.425
Debit value (R$ bn)	2011Q1–2025Q4	153.940	138.861	74.035	44.215	264.158
Pix share (%)	2011Q1–2025Q4	26.984	0.000	38.244	0.000	89.618
Credit share (%)	2011Q1–2025Q4	46.008	60.595	24.167	7.382	69.341
Debit share (%)	2011Q1–2025Q4	26.274	34.140	14.805	2.229	43.535
Pix/debit ratio	2011Q1–2025Q4	6.526	0.000	11.413	0.000	40.206
Selic (quarterly mean)	2005Q1–2025Q4	0.847	0.873	0.298	0.157	1.557
Inflation (quarterly mean)	2005Q1–2025Q4	0.449	0.415	0.273	-0.443	1.260

Note: Pix value and count statistics use positive completed quarters from 2020Q4 to 2025Q4. Payment-value and share statistics use the common comparison period through 2025Q4. Source: Author's calculations based on Banco Central do Brasil data.

4.2. Pix adoption over time

Pix expanded at an exceptional rate after its launch in 2020Q4. In that first partial operating quarter, Pix processed approximately R$149.9 billion through 176.2 million transactions. By 2021Q4, quarterly value had reached R$1.92 trillion and transaction count 3.84 billion. The expansion continued after the initial adoption phase: quarterly value reached R$3.34 trillion in 2022Q4, R$5.30 trillion in 2023Q4, R$7.71 trillion in 2024Q4, and R$10.22 trillion in 2025Q4. Over the same sequence, quarterly transaction count increased to 7.81 billion, 13.05 billion, 17.94 billion, and 22.29 billion, respectively.

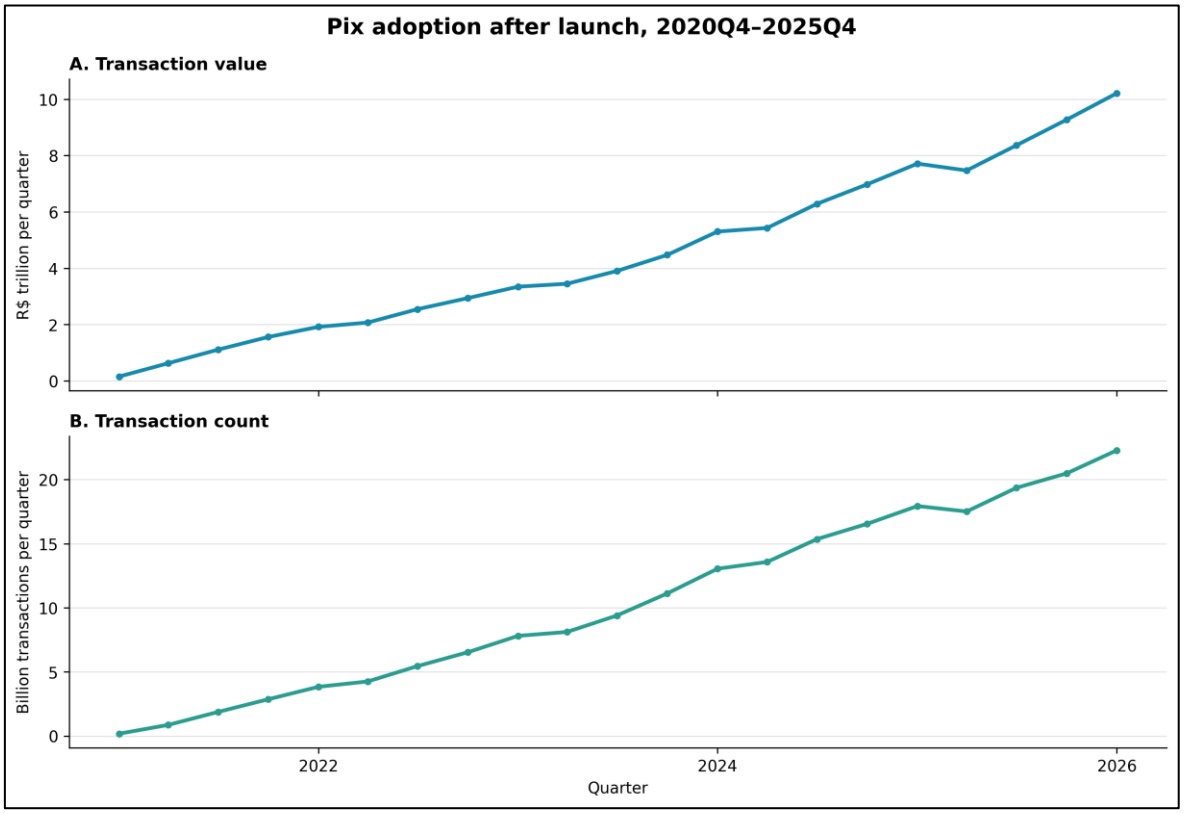


Figure 4.1 - Pix adoption after launch, 2020Q4-2025Q4

Note: The figure excludes partial 2026Q2 data and reports complete quarters only. Source: Author's calculations based on Banco Central do Brasil data.

Between 2020Q4 and 2025Q4, Pix value increased by a factor of approximately 68, while transaction count increased by a factor of approximately 126. The faster increase in count than in value reduced the implied average ticket from roughly R$851 in the launch quarter to about R$458 in 2025Q4, a decline of approximately 46 per cent. This pattern is consistent with diffusion from an initial set of relatively large transfers toward a broader range of routine, lower-value payments. It does not by itself reveal whether those transactions replaced cards, cash, bank transfers, boletos, or transactions that would not otherwise have occurred. It does, however, demonstrate that Pix became relevant at a scale capable of altering payment choices and the strategic environment faced by incumbent providers.

The milestone indicators reinforce this interpretation. Pix represented 19.6 per cent of the combined payment-value denominator in 2020Q4 and its value was equivalent to approximately 0.58 times debit-card value. One year later, its measured share was 71.3 per cent and its value was 7.44 times debit-card value. By 2025Q4, Pix represented 89.6 per cent of the denominator and its quarterly value was approximately 40.2 times debit-card value.

Table 4.3 - Selected Pix adoption milestones

Quarter	Pix value (R$ tn)	Pix count (bn)	Pix share (%)	Pix/debit ratio
2020Q4	0.150	0.176	19.6	0.58
2021Q4	1.916	3.836	71.3	7.44
2022Q4	3.343	7.807	78.8	12.65
2023Q4	5.300	13.046	84.4	20.46
2024Q4	7.713	17.937	87.6	29.67
2025Q4	10.215	22.287	89.6	40.21

Note: Value is reported in R$ trillion and count in billion transactions. Pix share uses the combined payment-value denominator; the Pix/debit ratio divides Pix value by debit-card value. Source: Author's calculations based on Banco Central do Brasil data.

These ratios measure scale, not direct merchant substitution. Total Pix value includes person-to-person transfers, business transfers, bill payments, tax payments, and other account-to-account uses that are not perfect alternatives to a debit-card purchase at a merchant. The Pix-to-debit ratio is nevertheless informative because debit is the card function with the closest payment-timing characteristics: both generally draw on funds available to the payer rather than extending revolving credit. A rising ratio therefore captures the increasing availability and practical relevance of an alternative immediate-payment rail, even though it overstates the volume that competes transaction for transaction with debit cards.

The shape of the adoption path also affects the econometric design. Pix exposure is almost monotonic over the observed post-launch period. Post-Pix time, Pix value, Pix share, and the Pix-to-debit ratio therefore move together closely. This makes it difficult to separate a generic post-2020 trend from the effect of increasing Pix intensity in a short aggregate time series. The issue is not a defect in the descriptive data; it is a consequence of a nationally introduced technology that diffused rapidly and persistently. Chapter 5 addresses the resulting collinearity by comparing timing-based and exposure-based specifications rather than treating any single proxy as definitive.

4.3. Evolution of payment values and shares

The expansion of Pix took place within a payment system in which card usage was also growing. In 2011Q1, quarterly credit-card value was approximately R$93.4 billion and debit-card value R$44.2 billion. By 2020Q4, these values had reached R$336.4 billion and R$258.5 billion. In 2025Q4, credit-card value was R$841.4 billion and debit-card value R$254.1 billion. Thus, the period of rapid Pix growth did not coincide with a general collapse in card value. Credit value continued to increase strongly, rising by approximately 150 per cent between 2020Q4 and 2025Q4. Debit value, by contrast, was broadly flat over the same endpoints, declining by approximately 1.7 per cent and fluctuating within a relatively narrow range after 2021.

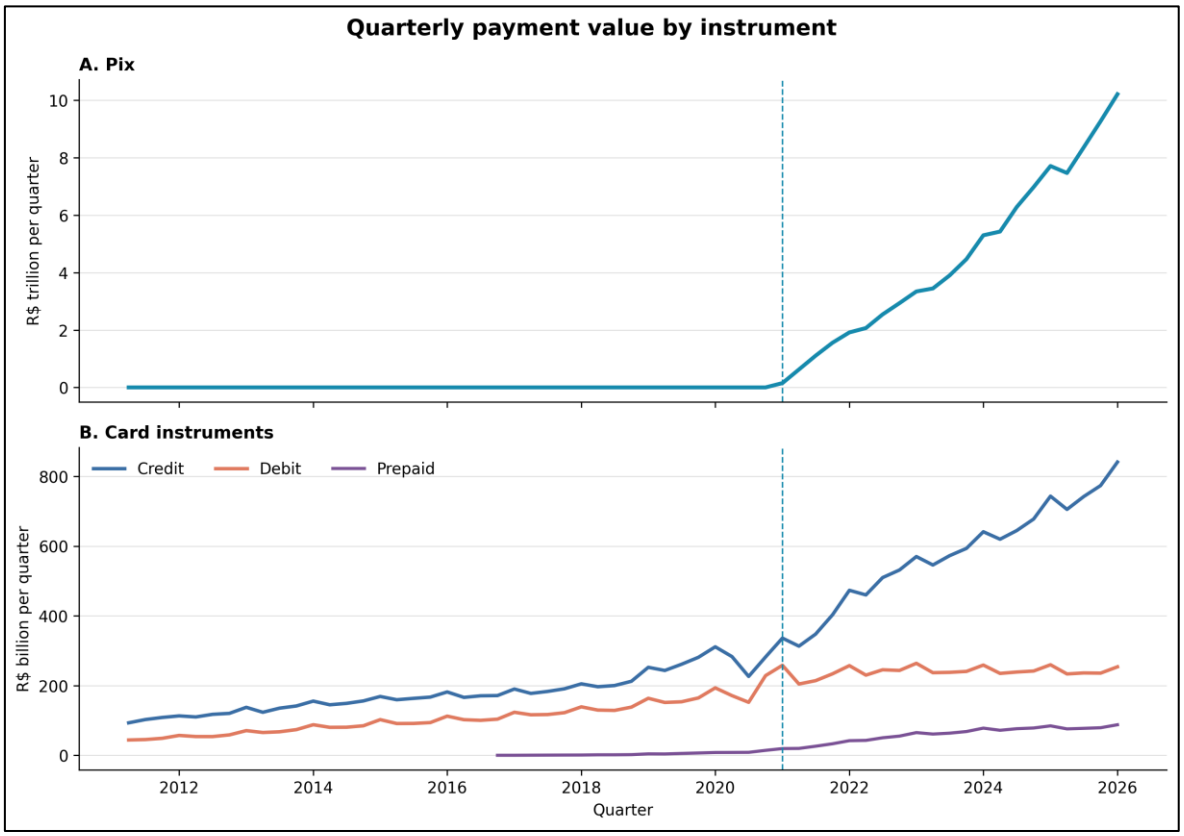


Figure 4.2 - Quarterly payment value by instrument

Note: Pix and card instruments are shown in separate panels because of their different scales. The comparison ends in 2025Q4. Source: Author's calculations based on Banco Central do Brasil data.

The separation of Pix and cards into two panels is necessary because the scale of Pix would otherwise compress the card series near the horizontal axis. The upper panel shows that Pix entered from zero and quickly became much larger in aggregate value than any individual card function. The lower panel reveals a more differentiated incumbent response. Credit continued along a pronounced upward path, including after the pandemic-related volatility of 2020. Debit rose strongly before and during the early Covid period but then ceased to display comparable sustained growth. Prepaid value, available from 2016Q3, also increased from a small base and remained much smaller than credit or debit.

This divergence is relevant to the substitution hypothesis. If Pix were a close replacement for debit but a weaker replacement for credit, one would expect debit to face greater pressure after 2020. The flattening of debit value alongside continuing credit growth is consistent with that possibility. It is not conclusive, however. Debit value may also reflect changes in household income, contactless adoption, e-commerce composition, card issuance, merchant acceptance, and the normalization of payment behavior after Covid. Moreover, a stable aggregate nominal value can conceal a decline in real terms or a shift in transaction count and average ticket. The descriptive series therefore provides a theoretically coherent motivation for separate debit and credit models, but not an identified estimate of substitution.

Payment shares display a much more dramatic change than absolute card values. Before Pix, credit accounted for most of the combined value denominator. Its share was 67.9 per cent in 2011Q1 and 60.2 per cent in 2018Q3. Debit increased from 32.1 per cent to 39.2 per cent over the same period. In 2020Q4, after Pix entered the denominator, the measured shares were 44.0 per cent for credit, 33.8 per cent for debit, and 19.6 per cent for Pix. By 2025Q4, they were 7.4 per cent, 2.2 per cent, and 89.6 per cent, respectively, with prepaid accounting for the small remaining proportion.

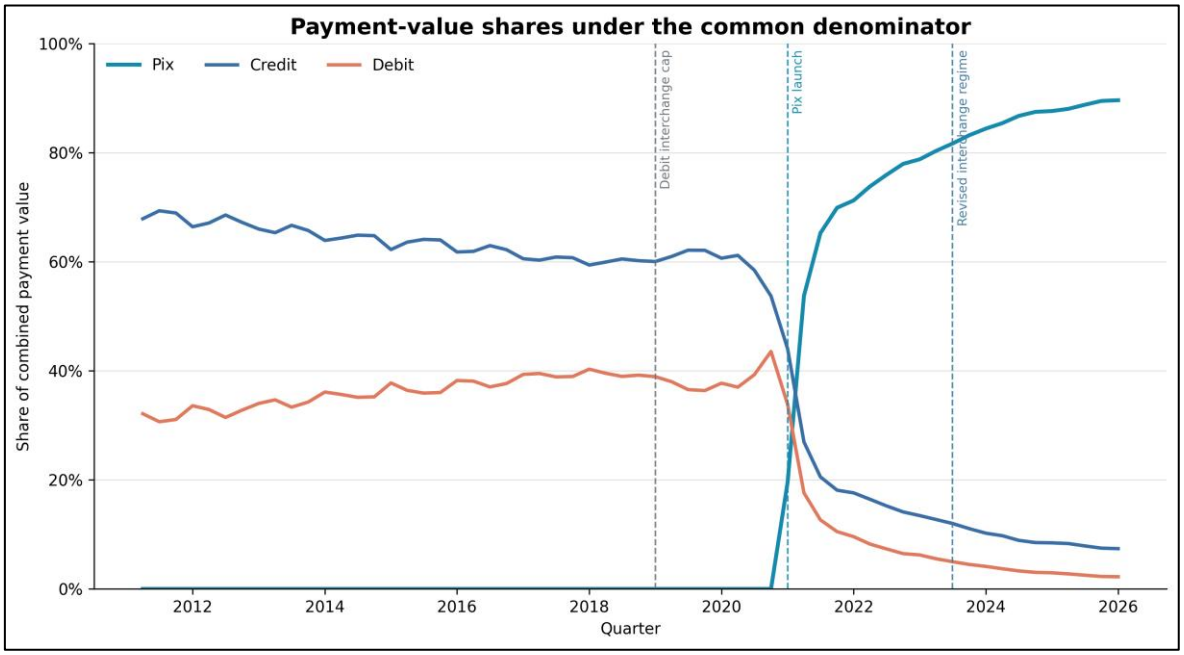


Figure 4.3 - Payment-value shares under the common denominator

Note: The shares are descriptive composition measures. Their common denominator mechanically contributes to negative co-movement between Pix and card shares. Source: Author's calculations based on Banco Central do Brasil data.

The figure demonstrates a clear reweighting of the measured payment system, but its construction imposes an important interpretive limitation. Pix, credit, debit, and prepaid shares use the same total-payment denominator. When Pix is added and grows rapidly, the measured card shares must fall mechanically unless card values grow at the same extraordinary rate. A negative association between Pix share and debit or credit share therefore combines genuine behavioral change with an accounting identity. In addition, the numerator for Pix includes transfers that do not have a card equivalent. The decline in card shares cannot be read as evidence that the same proportion of merchant purchases migrated from cards to Pix.

The contrast between levels and shares makes this limitation concrete. Credit share fell from 44.0 per cent in 2020Q4 to 7.4 per cent in 2025Q4 even though absolute credit value increased from R$336.4 billion to R$841.4 billion. The share decline therefore records the much faster expansion of Pix rather than a contraction of credit. Debit presents a different but still qualified pattern: its share fell sharply while its absolute value remained approximately stable. This combination is more compatible with relative displacement or foregone growth, but the aggregate data cannot determine how much debit value would have occurred in the absence of Pix.

For these reasons, the payment-composition analysis establishes two facts and leaves a third unresolved. First, Pix became the dominant component of the broad value denominator used in the dataset. Second, debit and credit became much smaller relative components of that denominator. Third, the amount of direct one-for-one substitution from card purchases to Pix remains unidentified. The formal payment-share regressions in Chapter 5 should consequently be interpreted as descriptions of aggregate composition rather than causal demand equations.

4.4. Evolution of MDR before and after Pix

The MDR series show that card-acceptance pricing was already changing long before the introduction of Pix. Debit MDR began at approximately 1.52 per cent in 2005Q1, reached a sample maximum of 1.61 per cent in 2009Q4, and then declined gradually. It stood at 1.40 per cent in 2018Q3, immediately before the debit interchange cap entered the quarterly indicator, and at 1.37 per cent in 2018Q4. By 2020Q3, the quarter immediately preceding Pix, debit MDR had fallen to 1.15 per cent. It was 1.16 per cent in 2020Q4 and ended the observed pricing sample at 1.08 per cent in 2025Q4.

Credit MDR followed a related but not identical trajectory. It began at approximately 2.87 per cent in 2005Q1, reached a maximum of 2.99 per cent in 2008Q4, and declined to 2.45 per cent by 2018Q3. It fell further to 2.15 per cent in 2020Q3 and was essentially unchanged at 2.16 per cent in the launch quarter. Credit MDR subsequently increased, reaching 2.36 per cent in 2022Q4, before declining to 2.05 per cent in 2025Q4.

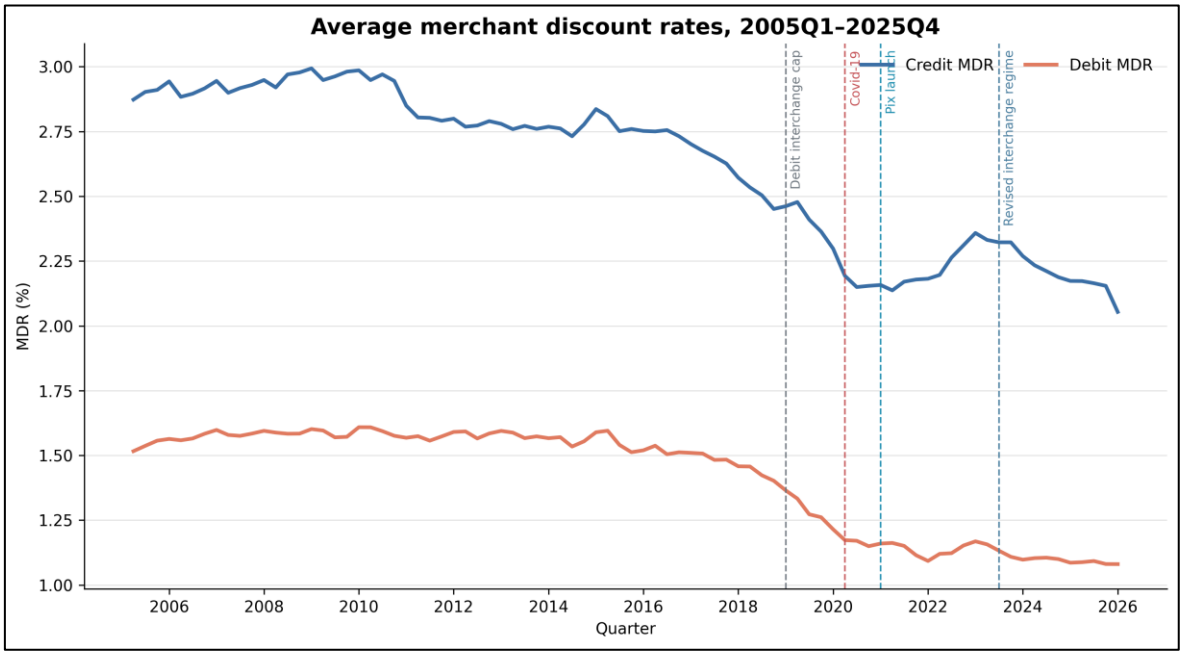


Figure 4.4 - Average debit and credit merchant discount rates, 2005Q1-2025Q4

Note: Vertical lines identify the debit interchange cap, the start of Covid-19, the Pix launch, and the revised interchange regime. Source: Author's calculations based on Banco Central do Brasil data.

Two features of the figure are central to the thesis. First, neither series begins its decline with Pix. The most visible compression in debit MDR occurs from the mid-2010s through 2020, and the 2018 interchange cap lies within this downward phase. Credit MDR also declines substantially before 2020. A simple comparison of early pre-Pix averages with post-Pix averages would therefore risk assigning a pre-existing trend to the new payment system.

Second, the launch quarter does not produce an unambiguous discontinuity in either MDR series. Debit MDR increases slightly from 1.150 per cent in 2020Q3 to 1.160 per cent in 2020Q4, while credit MDR moves from 2.154 per cent to 2.158 per cent. The economically relevant Pix hypothesis is therefore less likely to involve an instantaneous fee cut at launch than a gradual change in the subsequent pricing path as adoption, merchant acceptance, and strategic responses accumulated. This observation supports the use of both a post-launch level indicator and a post-launch slope term in the interrupted time-series models.

The post-Pix trajectories also differ by card function. Debit MDR remains in a narrow low range, falling below 1.10 per cent in several quarters and reaching its minimum at the end of the sample. Credit MDR first rises during 2021–2022 and only later resumes a downward movement. This divergence is consistent with the

argument that credit is less directly substitutable because it combines payment with financing, installments, rewards, and other services. At the descriptive stage, however, the pattern could also reflect macroeconomic conditions, changes in risk, merchant composition, or acquirer pricing strategies unrelated to Pix.

The difference between credit and debit MDR provides an additional summary of their relative pricing. The spread was generally between 1.3 and 1.4 percentage points in the first part of the sample. It narrowed over time, reaching approximately one percentage point around 2020, widened again as credit MDR increased in 2021–2023, and ended at approximately 0.97 percentage points in 2025Q4.

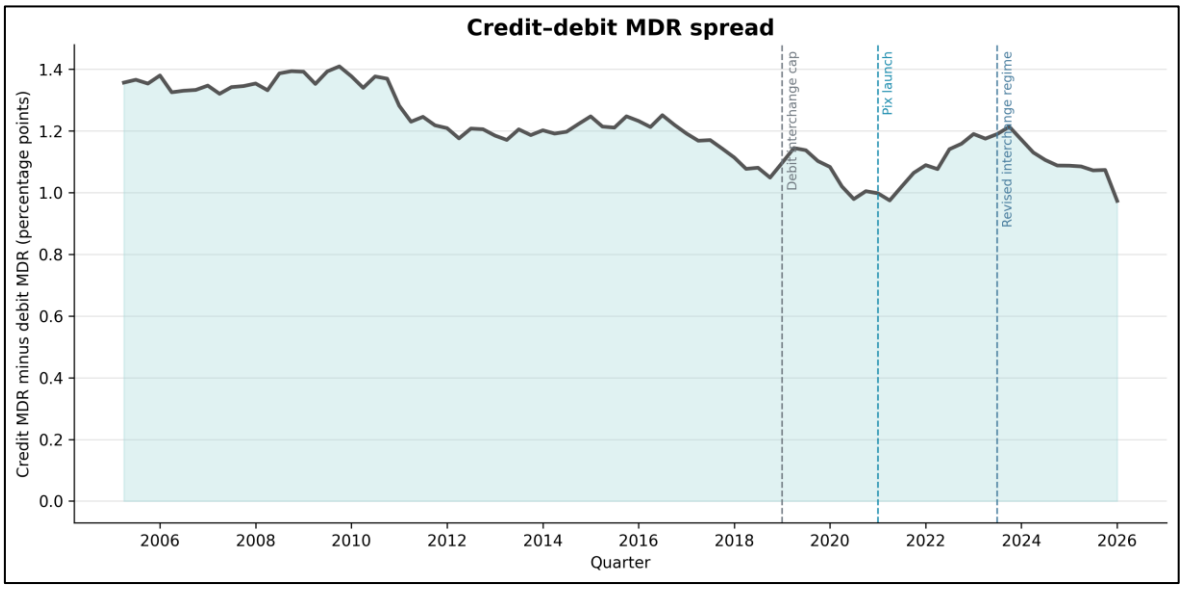


Figure 4.5 - Credit-debit MDR spread

Note: The spread equals credit MDR minus debit MDR and is expressed in percentage points. Source: Author's calculations based on Banco Central do Brasil data.

The spread does not exhibit a permanent collapse after Pix. Instead, it reflects the distinct movements of the two component rates: debit MDR had already fallen considerably before launch, while credit MDR temporarily increased afterward. This is another reason not to impose a common Pix effect across card functions. Separate debit and credit equations allow the estimates to reflect different product characteristics, cost structures, and competitive exposure.

Regime averages further clarify the chronology. Mean debit MDR was approximately 1.55 per cent in the pre-cap period, 1.24 per cent during the eight quarters from 2018Q4 to 2020Q3, and 1.12 per cent from 2020Q4 through 2025Q4. Mean credit MDR over the same regimes was approximately 2.82 per cent, 2.31 per

cent, and 2.22 per cent. The post-Pix averages are lower, but a substantial part of the total decline had already occurred by the time Pix launched. In particular, the reduction in debit MDR between the long pre-cap period and the post-cap/pre-Pix period is larger than the subsequent difference between the post-cap/pre-Pix and post-Pix averages. This descriptive sequencing makes the interchange regulation an essential control rather than a secondary robustness variable.

4.5. Pre/post-Pix descriptive comparison

A symmetric event window provides a more balanced descriptive comparison than full-period pre/post averages. The window used here compares the eight quarters from 2018Q4 through 2020Q3 with the eight quarters from 2020Q4 through 2022Q3. Using equal-length periods prevents the long early history of higher MDR from dominating the pre-Pix mean and focuses attention on observations closer to the intervention.

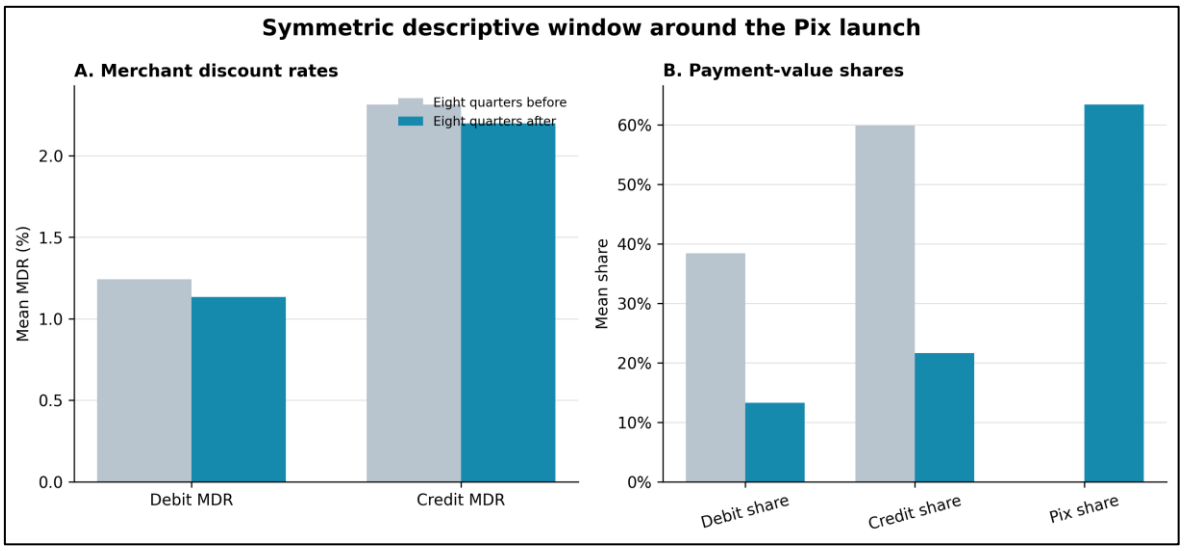


Figure 4.6 - Symmetric descriptive window around the Pix launch

Note: The before period is 2018Q4–2020Q3 and the after period is 2020Q4–2022Q3. Differences are descriptive and are not causal estimates. Source: Author's calculations based on Banco Central do Brasil data.

Table 4.4 - Eight-quarter comparison around the Pix launch

Metric	Eight quarters before	Eight quarters after	After minus before
Debit MDR (%)	1.243	1.134	-0.108
Credit MDR (%)	2.313	2.199	-0.114
Debit share (%)	38.4	13.3	-25.2
Credit share (%)	59.9	21.6	-38.3
Pix share (%)	0.0	63.4	+63.4
Pix/debit ratio	0.00	6.78	+6.78

Note: The before period is 2018Q4–2020Q3 and the after period is 2020Q4–2022Q3. Share differences are shown in percentage points; the Pix/debit ratio is a level ratio. Source: Author's calculations based on Banco Central do Brasil data.

Mean debit MDR was 1.243 per cent in the eight quarters before Pix and 1.134 per cent in the eight quarters after launch, a descriptive difference of -0.108 percentage points. Mean credit MDR declined from 2.313 per cent to 2.199 per cent, a difference of -0.114 percentage points. These changes are economically visible but small relative to the much larger movement in payment composition. Over the same windows, mean Pix share increased from zero to 63.4 per cent, debit share declined by 25.2 percentage points, credit share declined by 38.3 percentage points, and the mean Pix-to-debit ratio increased from zero to 6.78.

The comparison demonstrates that the payment environment changed far more abruptly than average MDR. If MDR adjusted one-for-one with the scale of the new payment alternative, the pricing break might be expected to resemble the sharp change in payment shares. Instead, the MDR series moved gradually and remained close to their pre-launch trajectories. This contrast is consistent with slow contractual adjustment, incomplete pass-through, differentiated card services, or competitive responses occurring through margins other than average MDR. It is also consistent with the possibility that much of the decline visible after 2020 reflects trends and interventions that predate Pix.

The event-window differences must not be interpreted as treatment effects. The before window begins with the debit interchange cap and includes the period in which debit MDR was already declining. The boundary between the windows also overlaps the Covid-19 shock and the subsequent recovery. Monetary conditions changed substantially during the after period, and payment behavior was unusually volatile. Moreover, Pix adoption increased continuously within the after

window rather than occurring as a single completed treatment in 2020Q4. The comparison is therefore a descriptive benchmark against which the controlled models can be judged.

The full-sample medians illustrate why an unrestricted pre/post comparison would be even less credible. Median debit MDR is approximately 1.57 per cent before Pix and 1.11 per cent afterward; median credit MDR is approximately 2.78 per cent before and 2.19 per cent afterward. These differences are larger than the symmetric-window differences because the pre-Pix period includes many early years in which MDR was structurally higher. They summarize historical change but do not isolate what occurred at the intervention. The formal ITS design addresses this problem by modeling the pre-existing trend rather than assuming that the entire pre-Pix period is a constant benchmark.

4.6. Seasonality, stationarity, and preliminary diagnostics

Quarterly seasonality appears limited in the unconditional MDR distributions. Mean debit MDR ranges from approximately 1.411 per cent in Q3 to 1.429 per cent in Q1, while mean credit MDR ranges from approximately 2.611 per cent in Q4 to 2.623 per cent in Q1. The median and interquartile distributions overlap substantially across calendar quarters. There is no visual evidence that one quarter consistently generates a large pricing shift relative to the others.

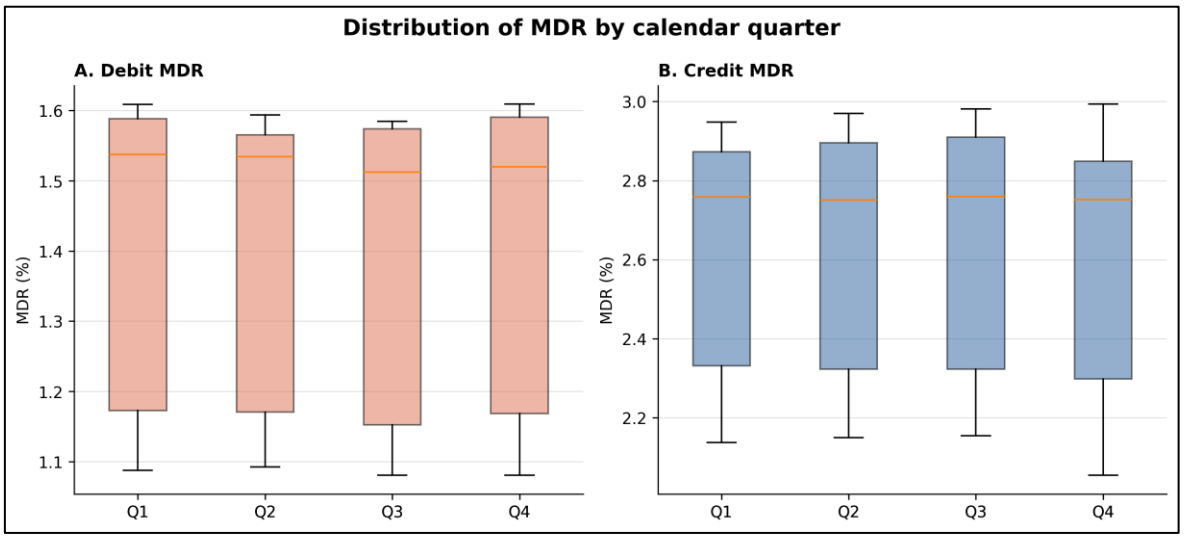


Figure 4.7 - Distribution of MDR by calendar quarter

Note: Boxes summarize the unconditional distributions of quarterly MDR observations through 2025Q4. Source: Author's calculations based on Banco Central do Brasil data.

The absence of strong unconditional seasonality does not make quarterly controls unnecessary. Seasonal effects can be small in the full distribution yet matter after trends, interventions, and macroeconomic conditions are controlled for. The econometric specifications therefore retain quarterly indicators. Their purpose is to prevent recurring within-year variation from being absorbed by the post-Pix terms, not to claim that seasonality is a major substantive driver.

The smoothness of the MDR paths suggests substantial serial dependence. Consecutive quarters are close to one another, and large changes usually unfold over several observations. Such persistence is economically plausible because merchant contracts, negotiated fee schedules, acquirer strategies, and the composition of merchants do not reset each quarter. It is also statistically important: if current MDR depends strongly on lagged MDR, a static segmented regression can mistake inherited pricing dynamics for an intervention effect. This motivates the dynamic ITS specifications that include lagged MDR and the differenced models that focus on short-run changes.

Formal stationarity tests confirm that the main level variables require caution. The augmented Dickey–Fuller (ADF) test fails to reject a unit root for debit MDR, credit MDR, Pix share, the Pix-to-debit ratio, debit share, and credit share at the 5 per cent level. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test rejects level stationarity for the same variables. The two tests therefore provide mutually reinforcing evidence that these series contain strong trends or highly persistent stochastic components. By contrast, the quarterly Selic and inflation controls are classified as stationary in the tested specifications.

Table 4.5 - Stationarity tests for the principal time-series variables

Variable	ADF p-value	KPSS p-value	Joint reading at 5%
Debit MDR	0.938	0.010	Non-stationary
Credit MDR	0.973	0.010	Non-stationary
Pix share	0.982	0.010	Non-stationary
Pix/debit ratio	0.930	0.010	Non-stationary
Debit share	0.878	0.010	Non-stationary
Credit share	0.837	0.010	Non-stationary
Selic	0.026	0.100	Stationary
Inflation	0.002	0.100	Stationary

Note: The ADF null hypothesis is a unit root; the KPSS null hypothesis is level stationarity. A joint non-stationary reading indicates failure to reject the ADF null and rejection of the KPSS null at 5 per cent. Source: Author's calculations.

Non-stationarity does not automatically invalidate an interrupted time-series model, because segmented trends explicitly represent deterministic changes in level and slope. It does mean that high fit and apparently significant coefficients in static level regressions can be misleading when trending variables move together. The problem is particularly relevant for the payment-share equations, where Pix share rises almost monotonically while card shares fall partly by construction. It is also relevant for exposure-augmented MDR models because the Pix-to-debit ratio and post-Pix time both increase throughout the same short period.

The diagnostic evidence therefore implies a staged interpretation. Static level models are useful for showing the unconditional segmented association and for maintaining continuity with the visual evidence. Dynamic models are needed to account for inherited pricing persistence. Differenced specifications test whether Pix-related results survive when common low-frequency trends are removed. Alternative time trends, logarithmic outcomes, and exposure proxies assess whether the conclusions depend on functional form or measurement. No single diagnostic selects a uniquely correct model, but together they establish why the robustness sequence in Chapter 5 is necessary.

4.7. Exploratory takeaways

The exploratory analysis produces six conclusions that structure the formal results. First, Pix adoption was rapid, sustained, and economically large. By 2025Q4, quarterly Pix value exceeded R$10 trillion and transaction count exceeded 22 billion. Its scale makes a competitive response by incumbent payment providers plausible.

Second, the aggregate payment mix changed profoundly. Pix became the dominant component of the broad payment-value denominator, while debit and credit shares declined sharply. This is strong evidence of system-level transformation, but not a direct measure of card substitution because the shares share a common denominator and Pix includes non-merchant transfers.

Third, absolute card values did not move uniformly. Credit value continued to grow strongly after Pix, whereas debit value broadly plateaued. The difference is consistent with stronger substitutability between Pix and debit than between Pix and credit, but it remains descriptive and may reflect other economic changes.

Fourth, MDR was declining before Pix. Debit and credit pricing both display long-run downward movement, and debit MDR fell substantially around the 2018 interchange cap. The launch of Pix does not coincide with a visually decisive immediate break. Any claimed Pix effect must therefore be distinguished from pre-existing trends and direct interchange regulation.

Fifth, equal-window pre/post comparisons show modest declines in average debit and credit MDR alongside very large changes in Pix adoption and payment shares. The timing is consistent with competitive pressure, but the magnitude and smoothness of the pricing response do not support a simple before/after causal interpretation.

Sixth, the key level series are persistent and non-stationary, while post-Pix timing and Pix intensity are closely related. These properties create a material risk of spurious or specification-sensitive coefficients in static regressions. The evidence justifies the progression from segmented level models to dynamic, differenced, nonlinear, logarithmic, and alternative-exposure specifications.

Overall, the descriptive record supports the premise that Pix transformed the competitive environment of Brazilian payments. It does not establish that this transformation independently reduced average debit or credit MDR. Chapter 5 therefore tests whether the apparent post-Pix pricing patterns remain after accounting for persistence, secular trends, macroeconomic conditions, Covid-19, seasonality, and interchange regulation.

5 Results

5.1. Overview of the empirical results

This chapter presents the empirical results of the thesis and evaluates whether the expansion of Pix affected merchant discount rates in the Brazilian acquiring market. The analysis follows the model sequence established in Chapter 3. It begins with payment-composition regressions, proceeds to baseline segmented interrupted time-series models, and then introduces dynamic, differenced, nonlinear, logarithmic, and exposure-based specifications. This sequence matters because the substantive conclusion changes when the statistical structure of the data is modeled more carefully. Simple level regressions initially produce several coefficients that appear consistent with downward competitive pressure from Pix. However, those estimates become weaker, change sign, or lose statistical significance once persistence, common trends, regulatory changes, and alternative functional forms are considered.

The results should therefore be read as an exercise in progressive empirical scrutiny rather than as a collection of independent regressions. The baseline models answer a transparent question: did MDR exhibit an immediate level change or a change in trend after the introduction of Pix? The dynamic models ask whether such changes remain once the substantial quarter-to-quarter persistence of merchant pricing is recognized. The differenced specifications test whether the conclusions survive when the analysis focuses on short-run changes instead of persistent levels. Finally, the nonlinear, logarithmic, interaction, and alternative-proxy models examine whether the findings depend on the assumed time path or on the measurement of Pix exposure.

Three principles guide interpretation. First, statistical significance is not equivalent to causal identification. Pix was introduced nationally in 2020Q4, so the analysis cannot compare treated and untreated Brazilian markets. The intervention date is clear, but other events occurred around the same period, including the Covid-19 shock, changes in monetary conditions, and payment-card regulation. Second, a significant coefficient from a model with severe residual autocorrelation or functional-form failure is not treated as conclusive. HAC standard errors improve inference under limited heteroskedasticity and serial correlation, but they do not

correct an incorrectly specified conditional mean. Third, robustness requires more than obtaining the same sign in one or two related regressions. A credible Pix effect should remain economically coherent when lagged MDR, regulatory controls, alternative trends, and different Pix proxies are introduced.

The unit of MDR is a percentage point. Accordingly, a coefficient of -0.05 means a reduction of 0.05 percentage points, equivalent to five basis points, rather than a five-percent decline. This distinction is important because many estimated changes are economically modest even when statistically significant. Share coefficients are expressed as fractions of the constructed payment-value total. Their interpretation requires additional caution because Pix, debit, and credit shares are calculated using the same denominator.

The core MDR sample covers 2005Q1 to 2025Q4. Dynamic specifications begin one quarter later because they include lagged MDR. Models using the Pix-to-debit ratio begin in 2011Q1 because the required card-value series is not complete over the earliest part of the MDR sample. The exposure models therefore use fewer observations and a different historical period. Their fit statistics cannot be compared mechanically with those of the full-sample equations. The principal comparison is instead whether the estimated Pix effects remain directionally and statistically coherent across the different samples and specifications.

The main result can be stated in advance. The models provide strong evidence that Pix transformed the aggregate composition of Brazilian payments. They do not provide equally strong evidence that this transformation caused a sustained reduction in average debit or credit MDR. Negative Pix-related coefficients appear in several simple specifications, but they are sensitive to persistence, trend definition, and exposure measurement. By contrast, the negative association between the 2018 debit interchange cap and debit MDR is considerably more stable. The remainder of this chapter explains how this conclusion emerges from the complete model sequence.

5.2. Payment-composition results

5.2.1. Pix share and debit share

The first payment-composition model uses debit share as the dependent variable and Pix share as the principal explanatory variable. The estimated Pix-share coefficient is -0.449 and is statistically significant at well below the 1% level. In numerical terms, a ten-percentage-point increase in Pix share is associated with an approximately 4.5-percentage-point reduction in the measured debit share, holding the included trend, macroeconomic controls, policy indicators, and seasonal effects

constant. The equation explains almost all variation in the dependent variable, with an adjusted R^2 above 0.99.

At first sight, this result appears to provide strong evidence of substitution from debit to Pix. That interpretation would nevertheless be too strong. Pix share and debit share are both constructed by dividing their respective payment values by the same aggregate payment-value denominator. When Pix value enters that denominator and expands rapidly, the measured debit share declines even if debit-card value remains stable or continues to grow. The negative coefficient therefore contains an arithmetic relationship in addition to any genuine behavioral substitution. Its very high precision partly reflects this construction.

The remaining coefficients reinforce the interpretation that the equation describes a changing payment composition rather than a clean substitution mechanism. The underlying time trend is positive, suggesting that debit share followed an upward conditional trend when Pix share is held fixed. The 2018 interchange-cap period is associated with a lower debit share, while the first and second quarters tend to have lower debit shares than the omitted fourth-quarter category. Covid and the 2023 regulatory regime are only marginally significant. Selic and inflation do not show statistically reliable relationships with debit share in this equation.

The residual diagnostics also require caution. The Durbin-Watson statistic is approximately 1.26, indicating positive residual persistence. The Pix-share and time variables have moderately elevated variance-inflation factors because both evolve strongly through the sample. HAC covariance reduces the risk that the reported standard errors are understated, but the remaining persistence means that the coefficient should not be treated as a fully dynamic estimate of payment substitution.

The defensible conclusion is consequently narrower than the raw coefficient suggests. Pix expansion coincided with a substantial decline in debit's share of the broad payment total. The regression does not establish that each increase in Pix represented an equivalent loss of debit transactions or merchant expenditure. Identification of that mechanism would require a dependent variable that does not share the Pix denominator, or merchant-purpose transaction data distinguishing purchases from transfers and other Pix use cases.

5.2.2. Pix share and credit share

The credit-share equation produces an even larger negative Pix coefficient, approximately -0.548, again with very high statistical significance. A ten-percentage-point increase in Pix share is therefore associated with an approximately

5.5-percentage-point decline in measured credit share. The model also has an adjusted R^2 above 0.99.

This result must not be interpreted as evidence that Pix displaced more credit than debit. Such a conclusion would conflict with the institutional differences between the instruments: Pix is an immediate account-to-account transfer, whereas credit cards provide financing, installment functionality, rewards, and liquidity management. The larger credit coefficient primarily reflects how the common denominator reallocates the relative shares as Pix becomes dominant. Debit and credit coefficients jointly absorb the expansion of Pix within the constructed payment total.

The control coefficients differ from the debit equation. The conditional time trend is negative, Covid is associated with a lower credit share, and the 2018 debit-cap period is associated with a higher credit share. The latter result may reflect relative movement within the payment mix: a policy directed at debit can alter the measured composition between card functions even when it does not directly regulate credit pricing. The first and second quarters are associated with higher credit shares than the fourth quarter. Selic and the 2023 regulatory indicator are positive only at the 10% significance level, while inflation is not statistically significant.

The credit-share diagnostics are weaker than those of the debit equation. The Durbin-Watson statistic is approximately 1.15, and the residual normality test rejects strongly. Normality is not required for HAC inference in a large-sample sense, but the combination of persistence, trend dominance, and a mechanically related denominator reinforces the need for descriptive language.

The two share equations therefore establish that Pix expansion accompanied a profound reweighting of the aggregate payment system. They do not establish the amount of economically meaningful card substitution. This distinction is central to the thesis. The composition evidence makes competitive pressure plausible because Pix became large enough to represent a credible outside option. It does not prove that merchants replaced debit or credit transactions in the proportions implied by the share coefficients.

5.2.3. Alternative measures of payment composition

The alternative debit-share models confirm the same broad pattern but also demonstrate its sensitivity to specification. When post-Pix time is used instead of Pix share, the estimated coefficient is strongly negative, indicating a rapid decline in debit share as the post-launch period progresses. When logged Pix value is used, the coefficient is again negative and highly significant. Pix share reproduces the main result, while the Pix-to-debit ratio also has a negative coefficient.

These alternative proxies do not solve the identification problem. The post-time equation has a Durbin-Watson statistic below 0.5, showing severe persistence. The logged-Pix-value equation is estimated using only 22 observations from the post-launch period and has a very high condition number, indicating that Pix growth is difficult to separate from the passage of time. The Pix-to-debit equation also has extremely persistent residuals. The similarity of the negative signs is therefore less informative than it initially appears: all proxies encode the same rapid and largely monotonic post-2020 expansion.

The payment-composition results are best summarized as follows. Pix clearly became much larger relative to debit and credit card values, and the measured card shares declined accordingly. The models cannot determine whether this occurred because card values fell, because card values grew more slowly than Pix, because Pix captured transactions previously conducted in cash, or because a large amount of Pix activity consisted of transfers that were never plausible card payments. The results support a system-transformation argument, but they do not independently identify the transaction-substitution channel required for a causal MDR mechanism.

Table 5.1 - Payment-composition regression coefficients

Outcome	Pix-share coefficient	HAC SE	p-value	95% CI	Adj. R^2	Interpretation
Debit share	-0.449	0.012	<0.001	[-0.473, -0.425]	0.996	Composition association; not direct substitution
Credit share	-0.548	0.014	<0.001	[-0.574, -0.521]	0.998	Composition association; not direct substitution

Note: HAC standard errors in parentheses are not shown because the table reports them in a separate column. The coefficients describe shares constructed with a common denominator and are not direct substitution estimates. *** $p < 0.01$. Source: Author's calculations.

5.3. Baseline segmented interrupted time-series results

5.3.1. Debit MDR baseline model

The baseline debit MDR model estimates a linear pre-Pix trend, an immediate level change beginning in 2020Q4, and a post-Pix slope change. It also controls for Selic, inflation, Covid, the 2018 debit interchange cap, the revised 2023 interchange regime, and quarterly seasonality.

The immediate post-Pix coefficient is -0.036 percentage points and is significant at the 5% level. This corresponds to an estimated decline of approximately 3.6 basis points at the intervention boundary, conditional on the other variables. The post-Pix slope coefficient is also negative, at approximately -0.002 percentage points per quarter, but is not statistically significant. The confidence interval permits both a moderate negative slope change and a small positive change. The joint test of the immediate and slope terms is significant, but this result is primarily driven by the immediate level coefficient rather than by evidence of a sustained change in trajectory.

If considered in isolation, the baseline estimate would be consistent with a limited immediate reduction in debit MDR around the introduction of Pix. It would not support a confidently accelerating decline because the slope term is imprecise. Even the immediate coefficient cannot automatically be attributed to Pix. The intervention quarter occurs during the Covid period and after a pre-existing decline in debit MDR associated with the acquiring-market and regulatory environment. The model controls observed events, but it cannot eliminate unobserved coincident changes.

Several control coefficients are statistically significant. The pre-Pix trend is negative, confirming that debit MDR was already declining before Pix. The 2018 debit-cap indicator has a large negative coefficient, and the Covid-period coefficient is also negative. The 2023 regulatory coefficient is negative at the 5% level in this baseline equation. Selic unexpectedly has a negative coefficient, while inflation is not significant. The seasonal indicators are also not significant.

The diagnostic evidence substantially weakens confidence in the baseline Pix coefficient. The Durbin-Watson statistic is below one, and the Breusch-Godfrey test strongly rejects the absence of residual autocorrelation. This means that unexplained positive and negative deviations persist across quarters. Because MDR is a slow-moving price series, such persistence is economically plausible, but it

violates the baseline model's implicit assumption that the included trend and controls adequately capture the time structure.

The baseline debit model is therefore informative but not decisive. It documents why a negative Pix interpretation initially appears plausible: the estimated series experiences a small downward displacement around launch. At the same time, it shows that the dependent variable contains substantial inertia and that debit MDR was already responding to regulation and long-run trends. A dynamic model is required before the immediate decline can be treated as an incremental intervention effect.

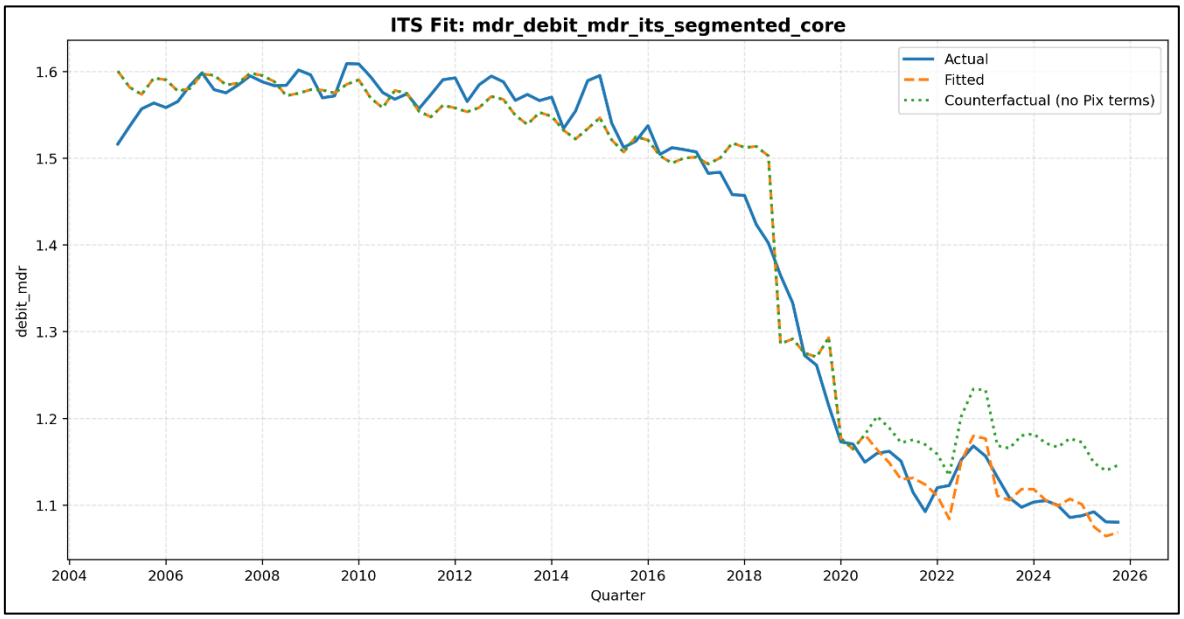


Figure 5.1 - Actual and fitted debit MDR in the baseline segmented ITS model

Note: The solid line reports observed debit MDR and the dashed line reports in-sample fitted values from the baseline segmented interrupted time-series model. The dotted comparison sets POST_PIX and TIME_AFTER_PIX to zero while retaining the observed time trend, regulatory indicators, macroeconomic controls, Covid indicator, and seasonal controls. It is a conditional model comparison rather than a causal untreated counterfactual. MDR is measured in percentage points.

5.3.2. Debit baseline model with Pix exposure

The exposure-augmented debit model adds the Pix-to-debit value ratio. This variable is intended to measure the intensity of potential competition rather than relying only on a launch date. The results change sharply. The post-Pix slope becomes much more negative and highly significant, while the Pix-to-debit

coefficient is positive and highly significant. The immediate level coefficient becomes positive and insignificant.

These estimates create an internally difficult interpretation. The negative slope would suggest that debit MDR declined progressively after Pix, but the positive exposure coefficient would suggest that quarters with greater Pix intensity were associated with higher debit MDR. Both variables rise strongly after 2020Q4. Their coefficients should therefore not be interpreted independently without considering their statistical overlap.

The variance-inflation factors make this problem explicit. The VIF for post-Pix time is approximately 358, and the VIF for the Pix-to-debit ratio is above 200. These values are not merely moderately elevated; they indicate that the regressors contain very little independent variation with which to estimate separate timing and exposure effects. The model is attempting to divide one dominant post-launch trend between two closely related variables. Small changes in sample or specification can consequently produce large changes in their signs and magnitudes.

The diagnostics also reject residual independence and the assumed functional form. The model therefore cannot be used to argue that the highly significant negative slope is stronger evidence than the baseline result. Its apparent precision is conditional on an unstable decomposition. The appropriate conclusion is that timing and Pix intensity cannot be separated reliably in a static level model.

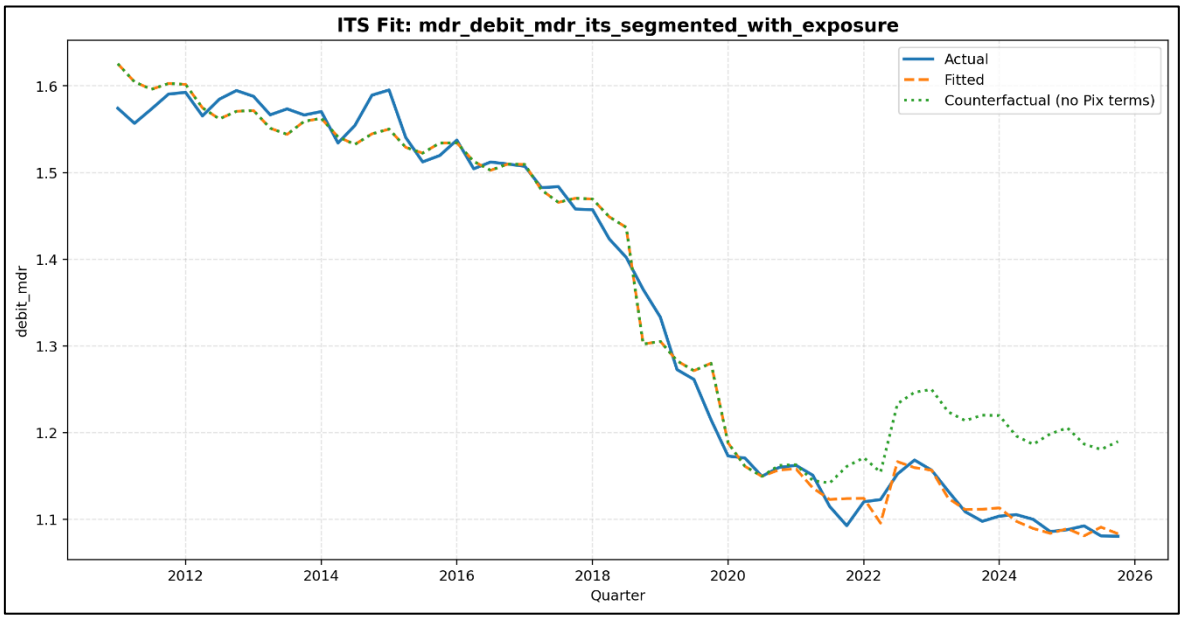


Figure 5.2 - Actual and fitted debit MDR in the baseline Pix-exposure model

Note: The solid and dashed lines report observed and fitted debit MDR. The dotted comparison sets POST_PIX, TIME_AFTER_PIX, and the Pix-to-debit ratio to zero while retaining the remaining observed regressors. Because post-Pix time and Pix exposure are extremely collinear, the separation between paths must not be interpreted as an identified causal effect. The exposure specification begins later than the core model because the Pix-to-debit ratio requires card-value data. MDR is measured in percentage points.

5.3.3. Credit MDR baseline model

The baseline credit equation does not display the same immediate negative pattern as debit. The post-Pix level coefficient is positive, approximately 0.061 percentage points, and is significant only at the 10% level. The slope-change coefficient is negative but statistically insignificant. The joint test of the post-Pix terms is also insignificant.

The point estimates could be described as a positive initial displacement followed by a somewhat more negative trend, but the uncertainty is too large to conclude that either component represents a structural Pix effect. The positive immediate coefficient is particularly inconsistent with a simple claim that the introduction of a low-cost payment alternative immediately compressed card acceptance prices across both card functions.

Inflation is positive and significant at the 5% level, while Selic is not significant. Covid and the 2018 cap-period indicator are strongly negative. The negative 2018 coefficient in a credit MDR equation does not imply that a debit regulation directly reduced credit MDR by the reported amount. It may instead capture common pricing developments, strategic repricing across card functions, or remaining long-run structure that the static equation does not model adequately.

The diagnostic failures are severe. Durbin-Watson is approximately 0.57, the Breusch-Godfrey test strongly rejects residual independence, and RESET rejects the functional form. The high R^2 therefore provides little reassurance. The model fits the level of the series but does not provide a satisfactory representation of how credit MDR evolves over time.

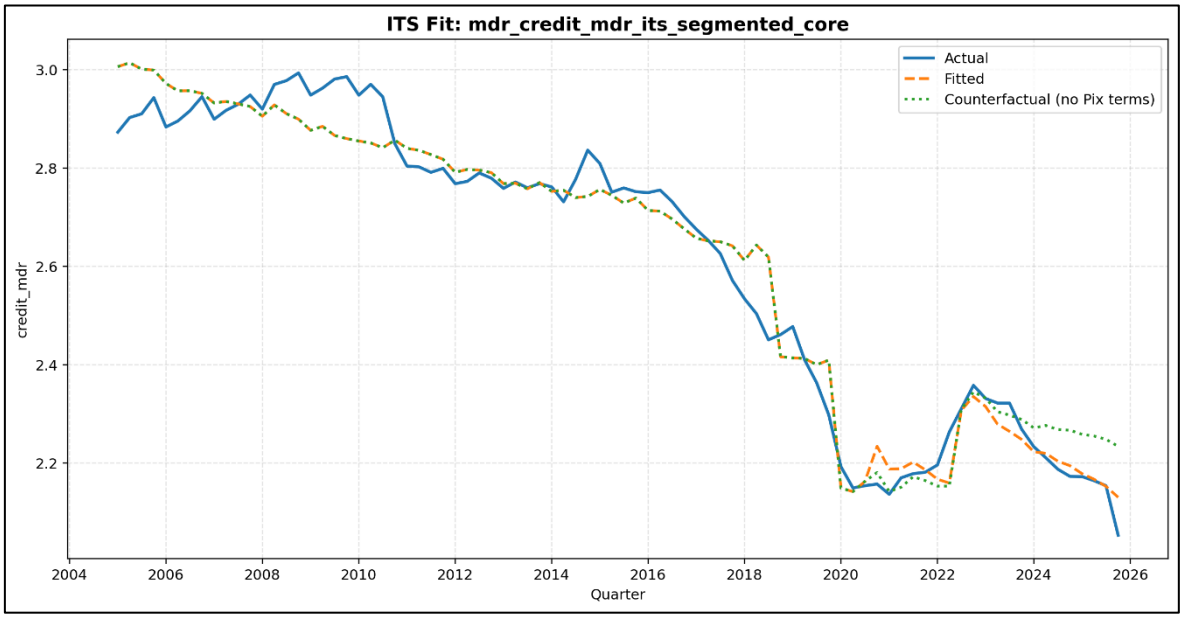


Figure 5.3 - Actual and fitted credit MDR in the baseline segmented ITS model

Note: The solid line reports observed credit MDR and the dashed line reports in-sample fitted values from the baseline segmented interrupted time-series model. The dotted comparison sets POST_PIX and TIME_AFTER_PIX to zero while retaining the other observed regressors. The high visual fit should be interpreted alongside the residual-autocorrelation and functional-form failures reported in Section 5.3.3. The dotted path is not a causal counterfactual. MDR is measured in percentage points.

5.3.4. Credit baseline model with Pix exposure

Adding the Pix-to-debit ratio produces a negative exposure coefficient that is significant at the 10% level. This estimate could be viewed as suggestive evidence that stronger Pix penetration coincided with lower credit MDR. However, neither the immediate level term nor the post-Pix slope is significant. The equation also produces significant positive Selic and inflation coefficients, a negative Covid coefficient, a negative 2018 cap-period coefficient, and a positive 2023 regulatory coefficient.

As in the debit exposure model, the post-time and exposure variables are extremely collinear. The residual autocorrelation and RESET tests also reject satisfactory specification. The negative exposure estimate therefore cannot be elevated to a substantive finding. Its sign is theoretically possible, but its statistical foundation is weak and it is not reproduced consistently in the later dynamic and differenced specifications.

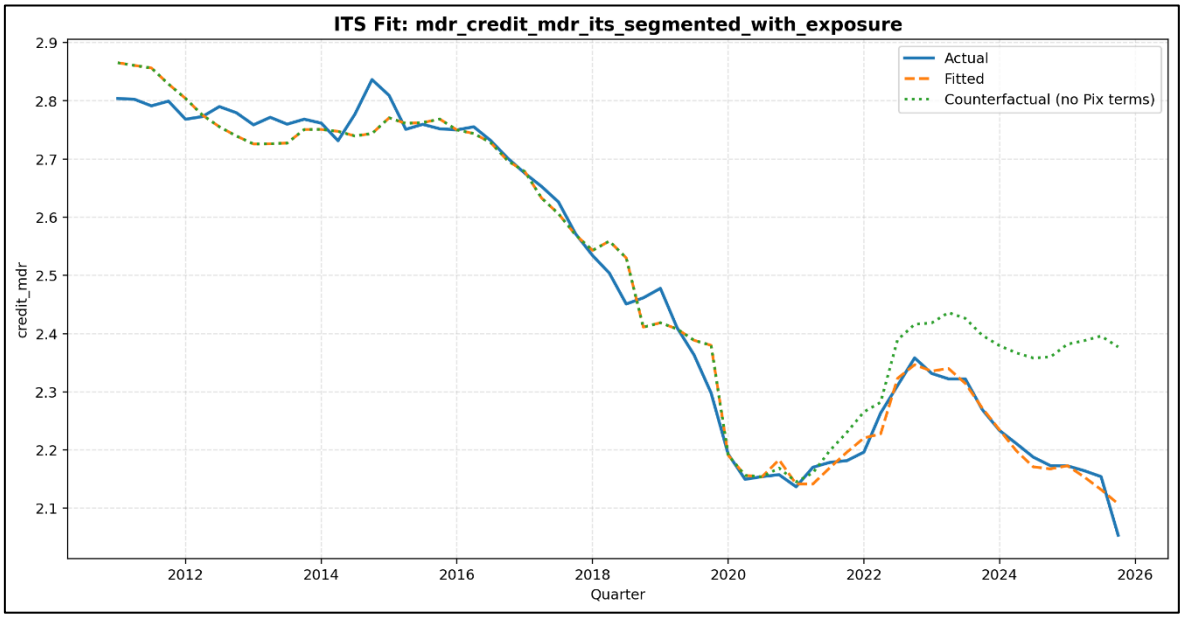


Figure 5.4 - Actual and fitted credit MDR in the baseline Pix-exposure model

Note: The solid and dashed lines report observed and fitted credit MDR. The dotted comparison sets POST_PIX, TIME_AFTER_PIX, and the Pix-to-debit ratio to zero while retaining the remaining observed regressors. The model's post-time and exposure terms are extremely collinear, and its residual diagnostics are weak. The dotted path is consequently a conditional specification comparison, not an estimate of the credit MDR path that would have occurred without Pix. MDR is measured in percentage points.

5.3.5. What the baseline stage establishes

The baseline stage explains why an initial reading of the data can support the thesis hypothesis. Debit MDR shows a significant negative level shift, the debit exposure model shows a significant negative post-Pix slope, and the credit exposure coefficient is marginally negative. These results align with the idea that Pix created a lower-cost outside option and pressured incumbent card pricing.

The same stage also reveals why that conclusion would be premature. Key coefficients change when the exposure variable is added, timing and exposure are nearly collinear, and all four baseline equations have material autocorrelation or functional-form weaknesses. Moreover, debit MDR had a negative pre-existing trend and a strong association with the 2018 interchange cap. The baseline models therefore identify suggestive temporal patterns, but they do not provide the most credible estimates of the Pix effect.

5.4. Dynamic ITS results: preferred specifications

5.4.1. Why persistence changes the interpretation

The dynamic models include the previous quarter's MDR. This modification is central rather than technical. Merchant discount rates are negotiated prices embedded in contracts, acquiring relationships, network-cost structures, and bundled financial services. They are unlikely to be independently reset each quarter. A large lag coefficient is therefore economically plausible and indicates gradual adjustment.

From an econometric perspective, omitting lagged MDR leaves persistent variation in the residuals. Intervention variables may then absorb that persistence, generating apparently significant level or slope changes. Adding lagged MDR asks a stricter question: after accounting for the price inherited from the previous quarter, is there an additional current-quarter displacement associated with Pix timing or exposure?

The dynamic core models are preferred because they substantially improve residual behavior while retaining a relatively interpretable specification. The exposure versions remain useful for testing the proposed competition mechanism, but their collinearity is much greater. The dynamic coefficients should be interpreted as short-run conditional effects. Long-run multipliers would depend heavily on the estimated lag and are not emphasized because the lag estimates are high and, for credit, the confidence interval approaches or exceeds unity.

5.4.2. Preferred debit MDR model

The lagged debit MDR coefficient is approximately 0.874 and is highly significant. This means that, conditional on the other regressors, a large proportion of the previous quarter's MDR level carries into the current quarter. The result confirms that debit MDR is strongly persistent and validates the decision to move beyond the static baseline model.

Once persistence is included, the central Pix coefficients change. The immediate post-Pix coefficient becomes positive, approximately 0.017 percentage points, and is significant only at the 10% level. The post-Pix slope coefficient becomes positive, approximately 0.001 percentage points per quarter, and is not statistically significant. Its confidence interval includes both a small negative effect and a larger positive effect.

This change is critical for the research question. The baseline negative immediate effect is not stable after lagged MDR is introduced, and the hypothesized negative slope is not identified. The preferred model does not show that debit MDR began

declining faster after Pix. Its central slope estimate points in the opposite direction, although the uncertainty prevents a conclusion that Pix caused MDR to rise.

The correct interpretation is therefore asymmetric. The model rejects a confident claim of negative Pix pressure, but it does not establish a positive causal effect. A positive coefficient may reflect remaining post-2020 factors, the specific trend counterfactual, or the difficulty of separating Pix from other nationwide developments. The empirical statement is that no negative incremental slope remains after conditioning on persistence and the observed controls.

The 2018 debit-cap coefficient remains negative and statistically significant, at approximately -0.048 percentage points. This represents a short-run reduction of about 4.8 basis points conditional on lagged MDR. Unlike the Pix terms, its sign is consistent across a broad range of debit specifications. The 2023 regulatory coefficient is also negative but reaches only the 10% significance level. These results suggest that direct regulation has a clearer relationship with debit MDR than the introduction of Pix.

The macroeconomic coefficients are not significant in the preferred debit model. Selic is close to zero, and inflation is negative but imprecise. The Covid coefficient also becomes essentially zero once lagged MDR and policy indicators are included. This differs sharply from the large negative Covid coefficient in the baseline equation and indicates that part of the baseline event effect reflected persistent movement already contained in the previous MDR level.

Seasonality is limited but not absent. The second quarter is associated with a statistically significant reduction in debit MDR relative to the fourth quarter, while the first and third quarters are not significant. The Q2 effect is reproduced in several debit robustness models, suggesting a recurring within-year pattern rather than a one-off result.

The diagnostic improvement is substantial. Durbin-Watson rises to approximately 1.81, and the Breusch-Godfrey test no longer rejects residual independence at the 5% level. Residual normality, heteroskedasticity, and stability tests are satisfactory. RESET is close to the 5% threshold, indicating that some functional-form uncertainty remains, but the specification is far more credible than the baseline model. The adjusted R^2 rises above 0.99, and the prediction errors fall by roughly half.

The preferred debit result can consequently be stated clearly: debit MDR is highly persistent; the 2018 interchange cap is associated with a significant reduction; and neither the immediate nor the slope component provides robust evidence that Pix reduced debit MDR. This is the central empirical finding of the thesis.

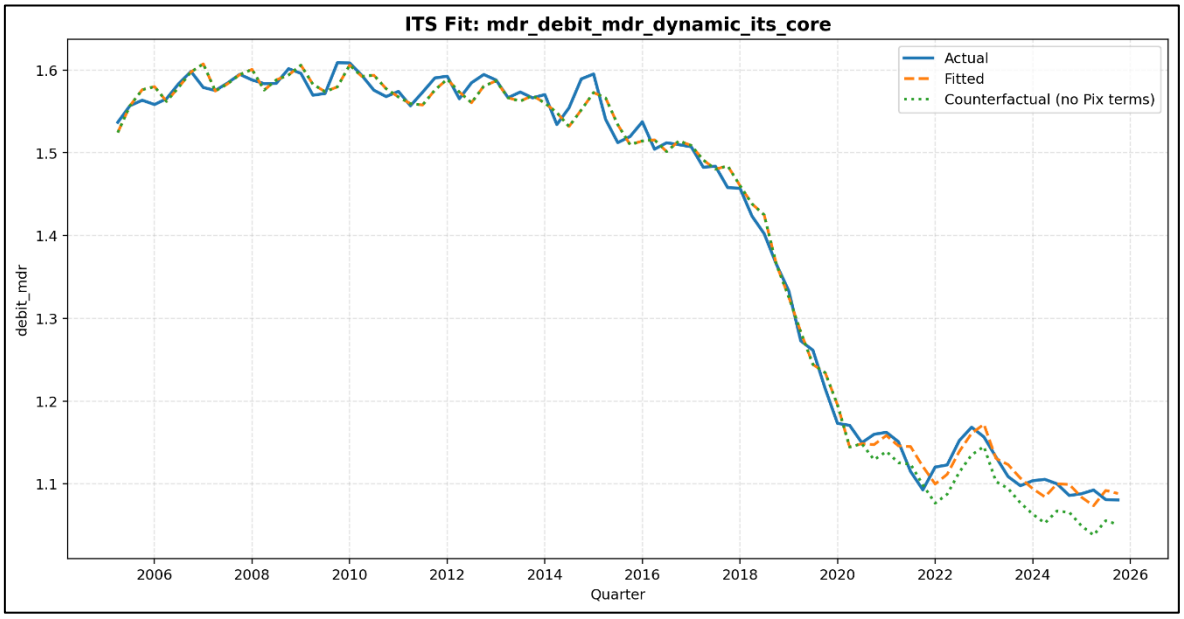


Figure 5.5 - Actual and fitted debit MDR in the preferred dynamic ITS model

Note: The solid line reports observed debit MDR and the dashed line reports one-quarter conditional fitted values from the preferred dynamic ITS model. The dotted comparison sets POST_PIX and TIME_AFTER_PIX to zero but retains observed lagged debit MDR and the remaining controls. It is not a recursively generated no-Pix trajectory or a causal counterfactual. MDR is measured in percentage points.

5.4.3. Dynamic debit model with exposure

The dynamic exposure equation asks whether debit MDR responds not merely to the passage of time after launch but to the magnitude of Pix relative to debit-card value. The lag coefficient remains large, approximately 0.756. The immediate post-Pix coefficient is positive and marginally significant, the post-Pix slope is negative but insignificant, and the Pix-to-debit coefficient is positive and insignificant.

The positive exposure point estimate should not be interpreted as evidence that Pix increased MDR. Its confidence interval includes negative and positive values, and the exposure variable is extremely collinear with post-Pix time. Equally, the negative slope should not be interpreted as hidden evidence of fee compression because it is also imprecise and conditional on the same unstable decomposition.

The regulatory pattern remains more stable. The 2018 cap coefficient is again negative and highly significant, close to five basis points. The 2023 coefficient is negative but insignificant. Q2 remains significantly negative. Inflation is borderline negative, while Selic is borderline positive.

Although Durbin-Watson remains close to 1.81, the Breusch-Godfrey and RESET tests reject at approximately the 5% level. More importantly, the VIF values for post-Pix time and Pix exposure exceed 400 and 250. These values demonstrate that the data contain insufficient independent variation to estimate separate timing and intensity effects with confidence. The model does not validate the competitive-exposure channel.

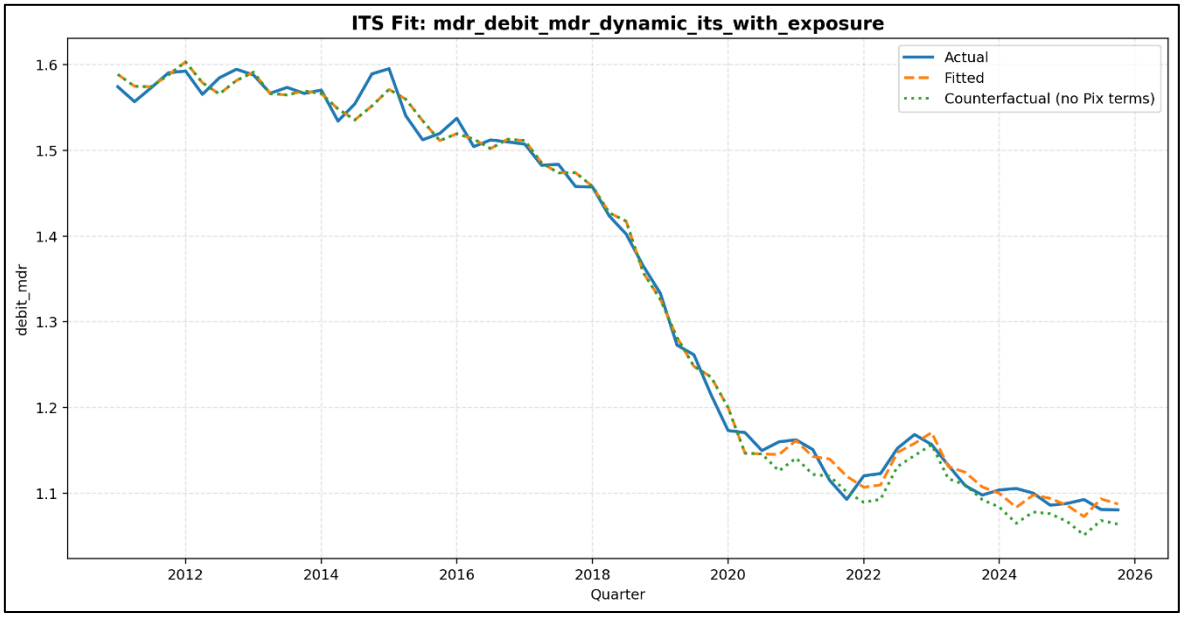


Figure 5.6 - Actual and fitted debit MDR in the dynamic Pix-exposure model

Note: The solid and dashed lines report observed and one-quarter conditional fitted debit MDR. The dotted comparison sets POST_PIX, TIME_AFTER_PIX, and the Pix-to-debit ratio to zero while retaining observed lagged debit MDR and the other controls. Extreme collinearity between post-Pix time and exposure prevents a stable decomposition of their effects. The dotted path is not a causal counterfactual. MDR is measured in percentage points.

5.4.4. Preferred credit MDR model

Credit MDR is even more persistent than debit MDR. The lag coefficient is approximately 0.943 and highly significant. The confidence interval extends slightly above one, implying that long-run multiplier calculations would be highly unstable. The appropriate focus is therefore the conditional short-run coefficient pattern.

The immediate post-Pix coefficient is positive and statistically significant, approximately 0.061 percentage points or 6.1 basis points. The slope-change coefficient is negative but very small and statistically insignificant. The joint post-

Pix test is significant because of the positive level coefficient, not because the model identifies sustained downward pressure.

This result does not mean that Pix caused credit MDR to increase. The model has no untreated control group, and the post indicator can capture omitted changes beginning in the same broad period. It does mean that the data reject a simple narrative of immediate credit-fee compression. After accounting for inherited pricing, the observed post-2020 level is higher than the model's conditional counterfactual, while the subsequent trajectory is not statistically different from the pre-Pix slope.

The regulatory coefficients differ from debit. The 2018 debit cap is not significant in the preferred credit equation, which is institutionally plausible because the regulation directly targeted debit interchange. The 2023 debit and prepaid interchange-regime coefficient is negative and significant at the 5% level, with an estimated magnitude of approximately -0.042 percentage points. This association should still be interpreted cautiously because the regulation did not directly target all credit MDR components, but it indicates a pricing shift around the later regulatory period.

Selic, inflation, and Covid are not statistically significant after persistence is included. Q1 is marginally negative, while Q2 and Q3 are insignificant. The absence of strong macroeconomic coefficients in the level equation does not imply that credit MDR is unrelated to monetary conditions. The differenced and exposure models provide stronger evidence of short-run Selic associations, discussed below.

The preferred credit model passes the principal diagnostics. Durbin-Watson is approximately 1.74, the Breusch-Godfrey test does not reject, RESET does not reject, heteroskedasticity tests are satisfactory, and the CUSUM test indicates stability. This is the cleanest primary model in the analysis. Its result is consequently important: a statistically credible credit equation identifies persistence and a positive post-level shift, but not a negative Pix-related slope.

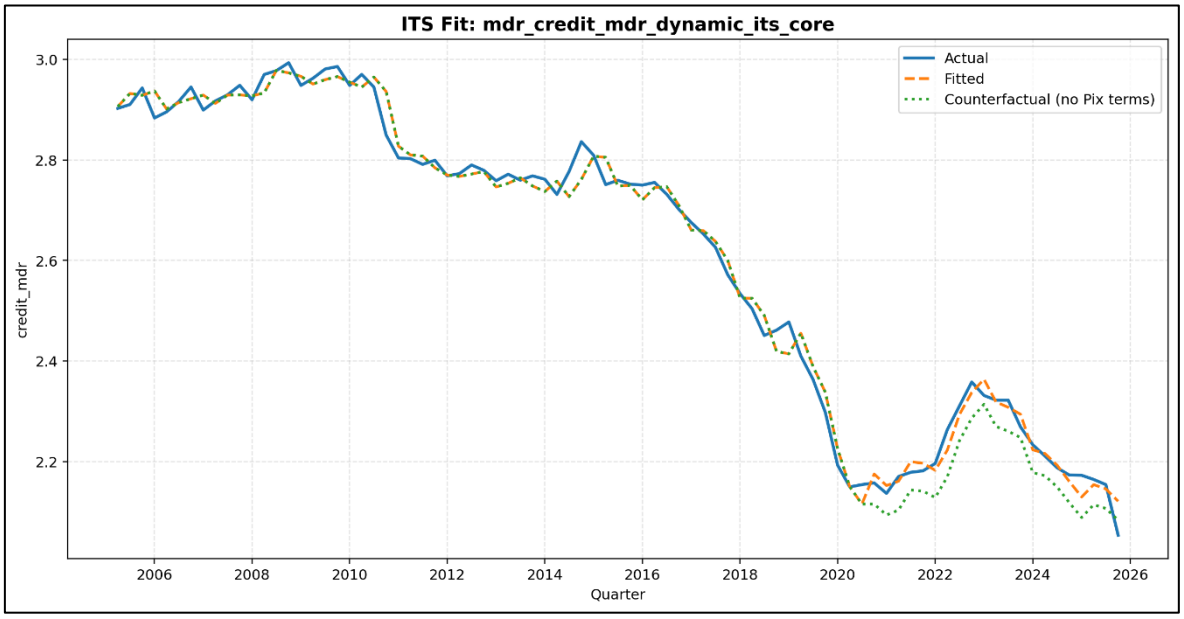


Figure 5.7 - Actual and fitted credit MDR in the preferred dynamic ITS model

Note: The solid line reports observed credit MDR and the dashed line reports one-quarter conditional fitted values from the preferred dynamic ITS model. The dotted comparison sets POST_PIX and TIME_AFTER_PIX to zero while retaining observed lagged credit MDR and all other controls. It is a conditional comparison and not a recursively simulated or causally identified no-Pix path. MDR is measured in percentage points.

5.4.5. Dynamic credit model with exposure

The exposure-augmented credit model produces a negative Pix-to-debit coefficient, but it is not statistically significant. The post-Pix slope becomes positive and insignificant, while the immediate post coefficient remains positive at the 10% significance level. The lag coefficient falls to approximately 0.769 but remains strongly significant.

Selic becomes positive and statistically significant in this shorter sample. This result is consistent with the possibility that higher interest rates increase the cost or value of credit-related services embedded in the acquiring ecosystem. Inflation remains insignificant. Neither the 2018 nor the 2023 regulatory indicator is statistically significant in this equation.

The residual diagnostics are generally acceptable, but the exposure and post-time regressors remain extremely collinear. A well-behaved residual process does not automatically imply that individual coefficients are well identified when regressors contain nearly the same information. The negative exposure sign is therefore

suggestive but not robust. It cannot support a conclusion that stronger Pix intensity reduced credit MDR.

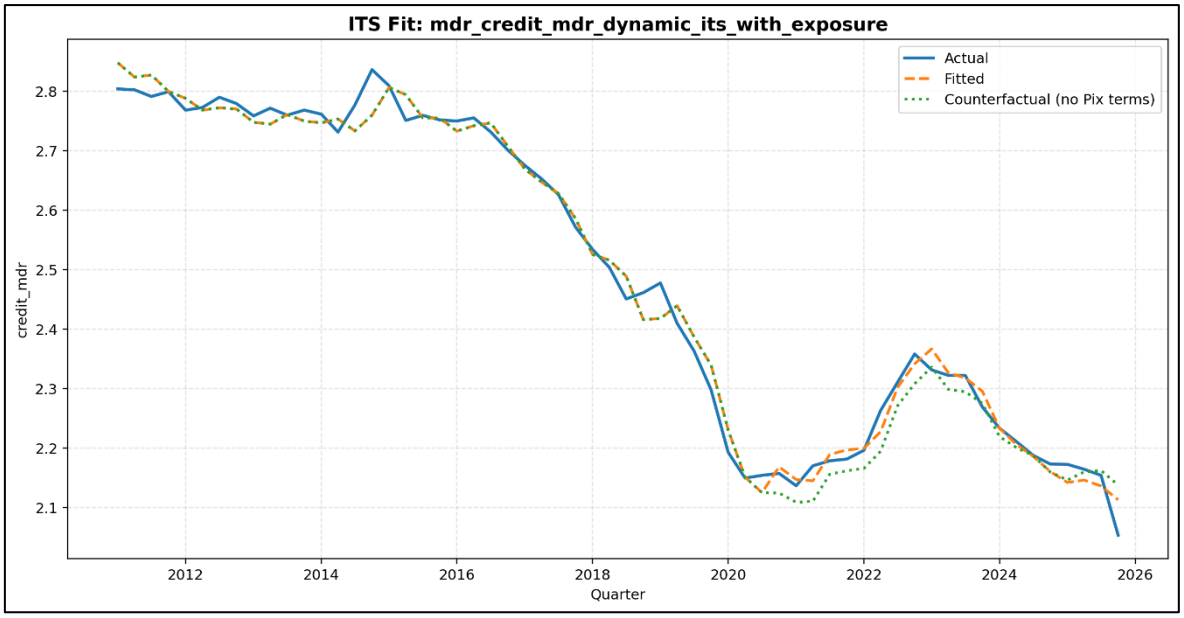


Figure 5.8 - Actual and fitted credit MDR in the dynamic Pix-exposure model

Note: The solid and dashed lines report observed and one-quarter conditional fitted credit MDR. The dotted comparison sets POST_PIX, TIME_AFTER_PIX, and the Pix-to-debit ratio to zero while retaining observed lagged credit MDR and the remaining controls. The exposure and post-time regressors are highly collinear, so the difference between paths is not an identified Pix effect. MDR is measured in percentage points.

5.4.6. Debit versus credit in the preferred models

The comparison between debit and credit does not produce the originally expected asymmetry. The theoretical hypothesis predicted stronger downward pressure on debit because Pix more closely replicates an immediate account-funded payment. In the preferred models, however, debit's post-Pix slope is positive and insignificant, while credit's slope is negative and insignificant. Neither provides evidence of sustained compression.

The two outcomes differ in their level terms and regulatory relationships. Credit has a significant positive post-level coefficient, whereas debit's level coefficient is only marginally positive. The 2018 debit cap has a clear negative debit effect and no credit effect in the preferred equations. The 2023 regime is more visible in credit than debit. These differences indicate that debit and credit pricing respond to

distinct institutional and market structures, but they do not establish Pix-driven asymmetric competition.

The preferred-model comparison also demonstrates the importance of inertia. Both MDR series have large lag coefficients. Credit is particularly persistent, consistent with its more complex product bundle and potentially slower repricing. Debit is somewhat less persistent, but its remaining variation is more clearly related to the earlier interchange cap than to the Pix intervention terms.

Table 5.2 - Baseline and preferred dynamic MDR estimates

Model	POST_PIX	TIME_AFTER_PIX	Lagged MDR	2018 cap	Adj. R^2
Debit baseline	-0.036** (0.017)	-0.002 (0.002)	—	-0.220*** (0.034)	0.974
Credit baseline	0.061* (0.037)	-0.008 (0.005)	—	-0.184*** (0.048)	0.955
Debit preferred dynamic	0.017* (0.010)	0.001 (0.001)	0.874*** (0.064)	-0.048*** (0.014)	0.994
Credit preferred dynamic	0.061*** (0.022)	-0.001 (0.003)	0.943*** (0.060)	-0.007 (0.026)	0.990

Note: HAC standard errors are in parentheses. MDR coefficients are percentage points. * p < 0.10; ** p < 0.05; *** p < 0.01. The dynamic coefficients are conditional short-run estimates, not unconditional total effects. Source: Author's calculations.

5.5. Robustness analysis

5.5.1. Differenced models

The differenced models focus on quarter-to-quarter changes rather than MDR levels. This transformation reduces the influence of common trends and substantially lowers multicollinearity. It also changes the economic question. Instead of asking whether post-Pix MDR occupies a different level or trajectory, the model asks whether changes in the Pix path coincide with contemporaneous changes in MDR.

In the core debit-change equation, the post-Pix change coefficient is negative but statistically insignificant. Changes in Selic and inflation are also insignificant. The

transitions into the Covid period and the 2018 debit-cap regime are both associated with significant negative changes in debit MDR. Q2 remains negative and significant. The 2023 transition and the remaining seasonal terms are not significant.

The debit differenced equation has much lower explanatory power than the level models. This is expected because differencing removes the highly predictable persistent component. Its residual autocorrelation and functional-form diagnostics are acceptable, although CUSUM indicates instability over the full sample. The model nevertheless provides no evidence that the post-Pix path generated systematic quarterly reductions in debit MDR.

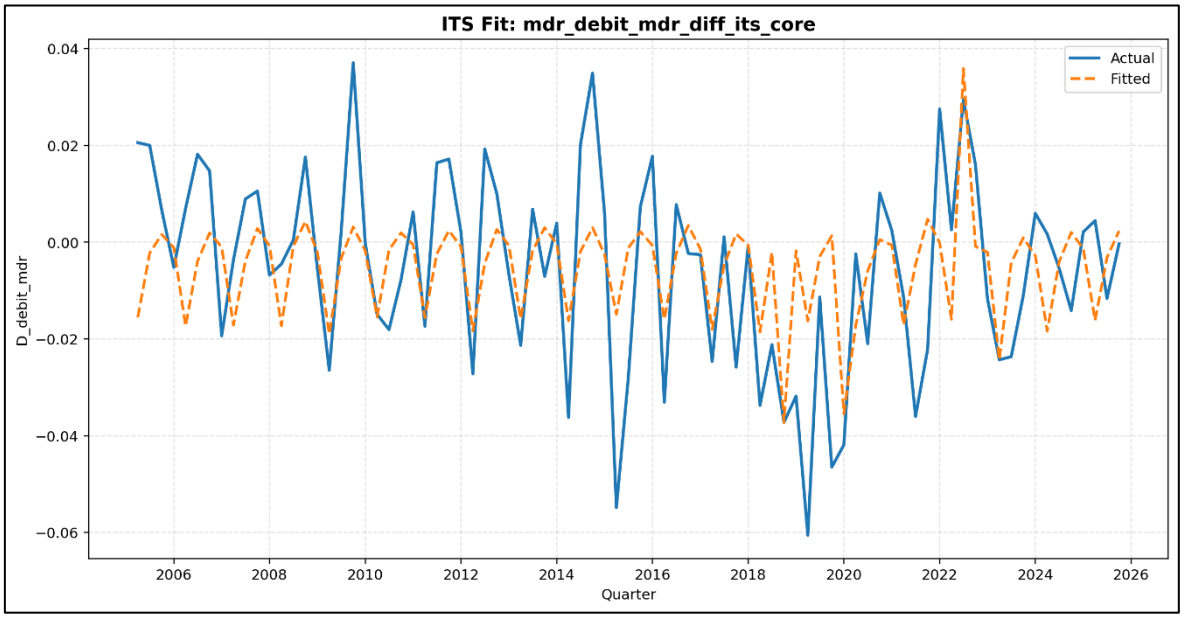
Adding the change in the Pix-to-debit ratio does not alter that conclusion. Both the post-time change and exposure change are statistically insignificant, and the exposure coefficient is positive. Covid and the 2018 cap remain strongly negative, and Q2 remains significant. The residual diagnostics and stability test are satisfactory, and VIF values are far lower than in the level exposure equations.

This is an important robustness result. The absence of a Pix effect cannot be attributed solely to multicollinearity in levels. When common trends are removed and the exposure variables become easier to separate, faster Pix growth still does not coincide with significant contemporaneous reductions in debit MDR.

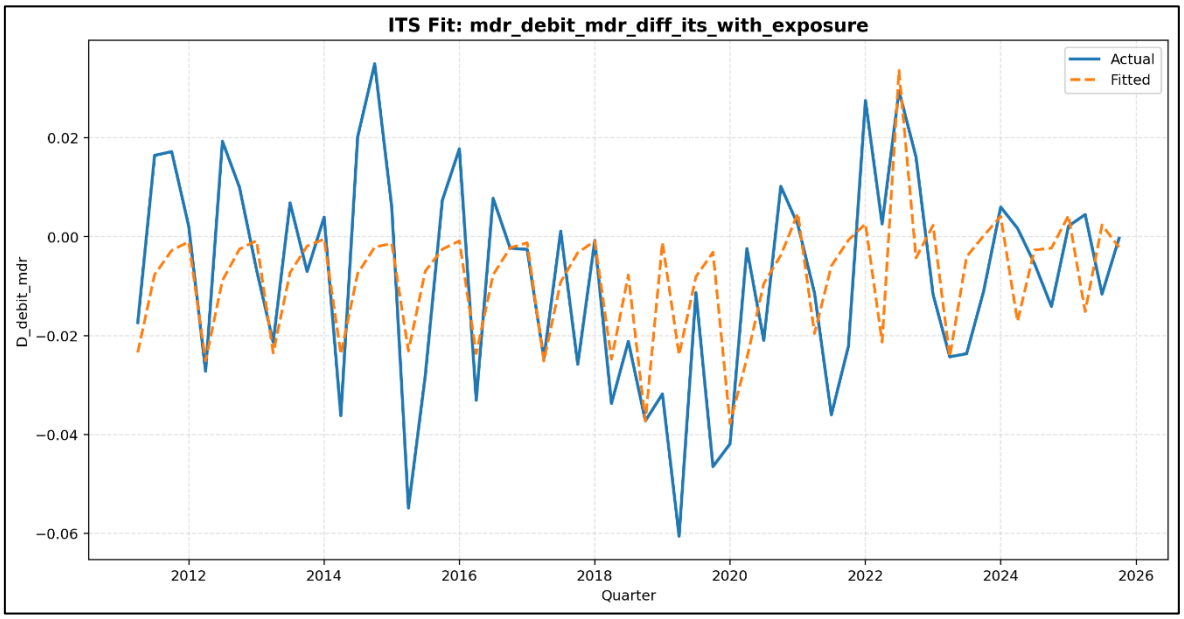
The credit differenced models produce a similar conclusion for Pix but a different pattern for macroeconomic controls. Neither the post-Pix change nor the change in Pix exposure is statistically significant. Changes in Selic and inflation are positive and significant, indicating that short-run credit MDR adjustments are more closely associated with macro-financial conditions. The Covid transition is strongly negative.

The differenced 2018 debit-cap indicator is positive in the credit equations. This should not be interpreted as a direct causal increase in credit MDR caused by a debit regulation. A differenced event dummy identifies the discrete transition into a regime, and the coefficient may capture coincident repricing, relative movement between debit and credit, or strategic adjustment across card products. The important point for the thesis is that the credit change models identify macroeconomic and event transitions, not a Pix-driven reduction.

The exposure-differenced credit model passes the principal residual and stability tests. Its Pix-to-debit change coefficient remains insignificant. This strengthens the conclusion that the absence of a credit Pix effect is not merely the consequence of poor diagnostics in the level models.



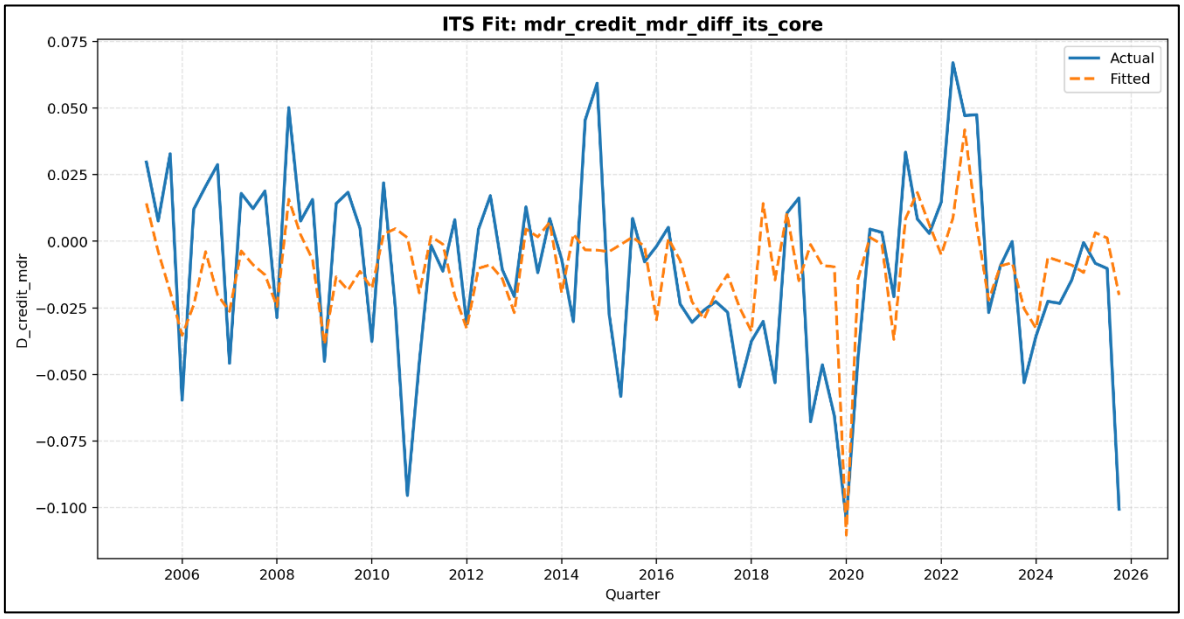
(a) Core differenced ITS model



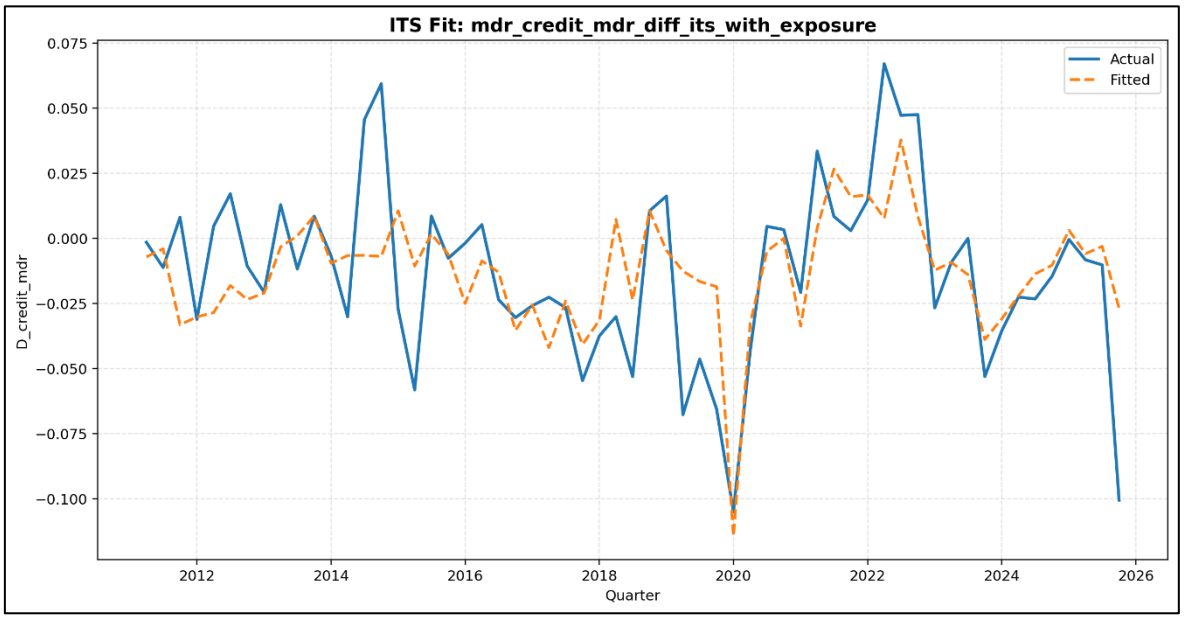
(b) Differenced model with change in Pix exposure

Figure 5.9 - Actual and fitted quarterly changes in debit MDR

Note: The solid and dashed lines report observed and fitted quarter-to-quarter changes in debit MDR. Panel (a) uses the core differenced specification; panel (b) adds the change in the Pix-to-debit ratio. The pipeline does not construct a no-Pix path for the differenced regressor names. Low explanatory power is expected because differencing removes the persistent level component. Changes are measured in percentage points.



(a) Core differenced ITS model



(b) Differenced model with change in Pix exposure

Figure 5.10 - Actual and fitted quarterly changes in credit MDR

Note: The solid and dashed lines report observed and fitted quarter-to-quarter changes in credit MDR. Panel (a) uses the core differenced specification; panel (b) adds the change in the Pix-to-debit ratio. The pipeline does not generate a no-Pix path for these differenced specifications. The figures visualize short-run fit and should not be compared mechanically with the R-squared of MDR level models. Changes are measured in percentage points.

5.5.2. Nonlinear trends

The quadratic-trend models allow MDR to follow a curved long-run path. This addresses the possibility that the linear ITS specification incorrectly attributes natural acceleration or deceleration to the intervention terms.

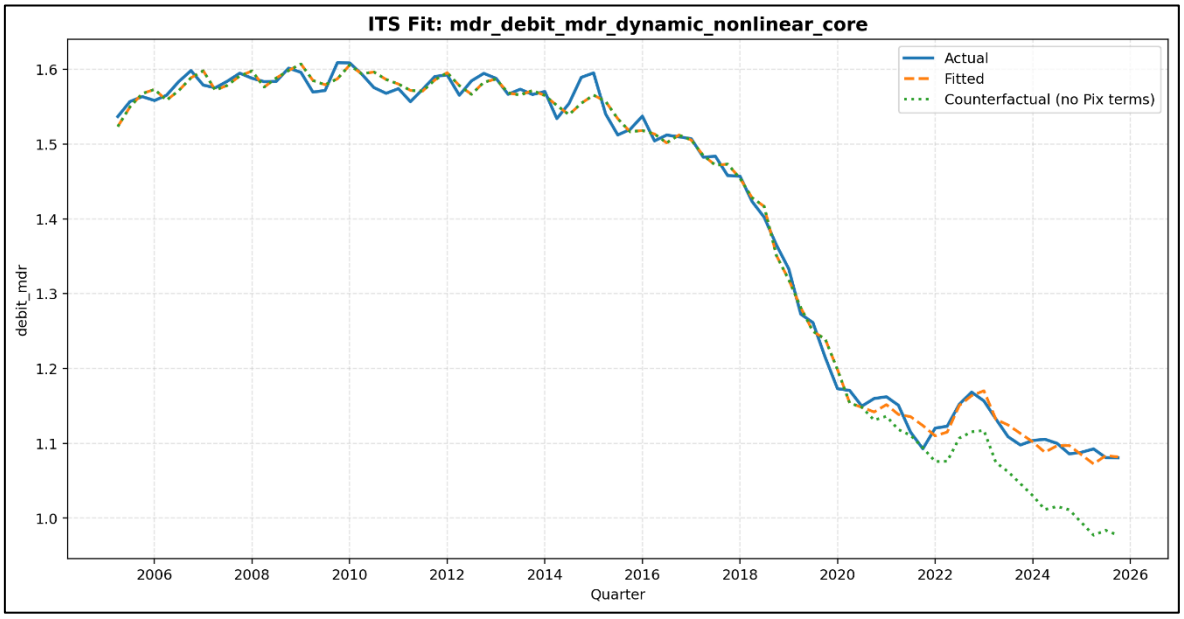
For debit MDR, the linear time term is positive and the squared term is negative, implying a concave trajectory. The post-Pix slope becomes positive and statistically significant, while the immediate level term remains insignificant. The model therefore implies that, relative to the estimated curved counterfactual, the post-Pix path is less downward or more upward than expected.

This positive slope must not be interpreted as evidence that Pix raised debit MDR. The quadratic time terms, lagged MDR, and post-time variables are extremely collinear, and the Breusch-Godfrey test still detects residual autocorrelation. The result is instead evidence of specification sensitivity. A negative Pix slope is not invariant to allowing curvature; it reverses sign and becomes positive.

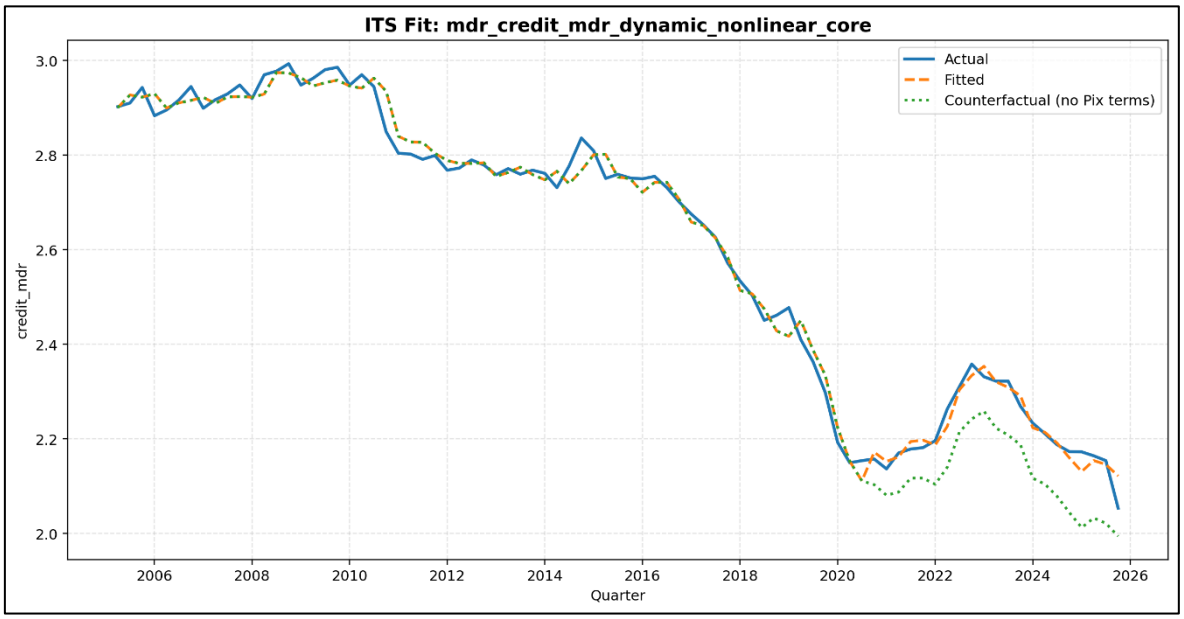
The 2018 debit cap remains negative and highly significant in the nonlinear debit model. Q2 and Q3 are also negative. The lag remains substantial. Thus, the nonlinear specification continues to support regulation, persistence, and seasonality while contradicting a robust negative Pix slope.

The nonlinear credit equation also estimates a concave time path. The immediate post coefficient remains positive and significant, and the slope coefficient is positive but insignificant. Selic is positive and significant, while the main regulatory indicators are not. The model passes the principal diagnostics and slightly improves fit relative to the preferred linear dynamic credit equation.

Allowing nonlinear time therefore does not reveal hidden credit-fee compression. It preserves the positive post-level component and leaves the slope statistically unresolved. Across both outcomes, curvature weakens rather than strengthens the central hypothesis.



(a) Debit MDR



(b) Credit MDR

Figure 5.11 - Actual and fitted MDR under dynamic nonlinear time trends

Note: The solid and dashed lines report observed and one-quarter conditional fitted MDR from models with linear and quadratic time terms. The dotted comparison sets POST_PIX and TIME_AFTER_PIX to zero while retaining the estimated nonlinear time path, observed lagged MDR, and other controls. It is sensitive to the assumed curved counterfactual trend and is not a causal no-Pix path. MDR is measured in percentage points.

5.5.3. Logarithmic models

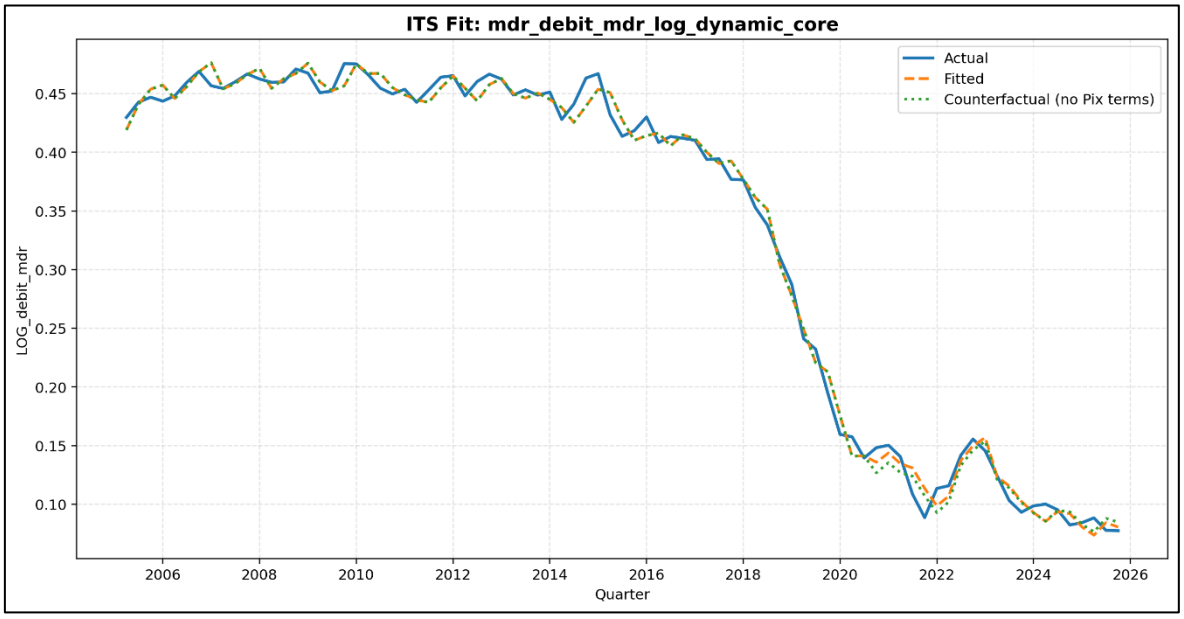
The log models test whether results depend on measuring MDR changes in percentage-point levels. In a logged outcome, small coefficients can be interpreted approximately as proportional changes, although the inclusion of lagged level MDR means that the equations are not pure autoregressive log models.

The log debit core equation estimates a small positive immediate post effect and a small negative slope effect, but neither is statistically significant. The 2018 cap is associated with an approximate 3.8% reduction in debit MDR, and the 2023 regime with an approximate 1.8% reduction. Q2 is again negative. Macroeconomic and Covid coefficients are not significant.

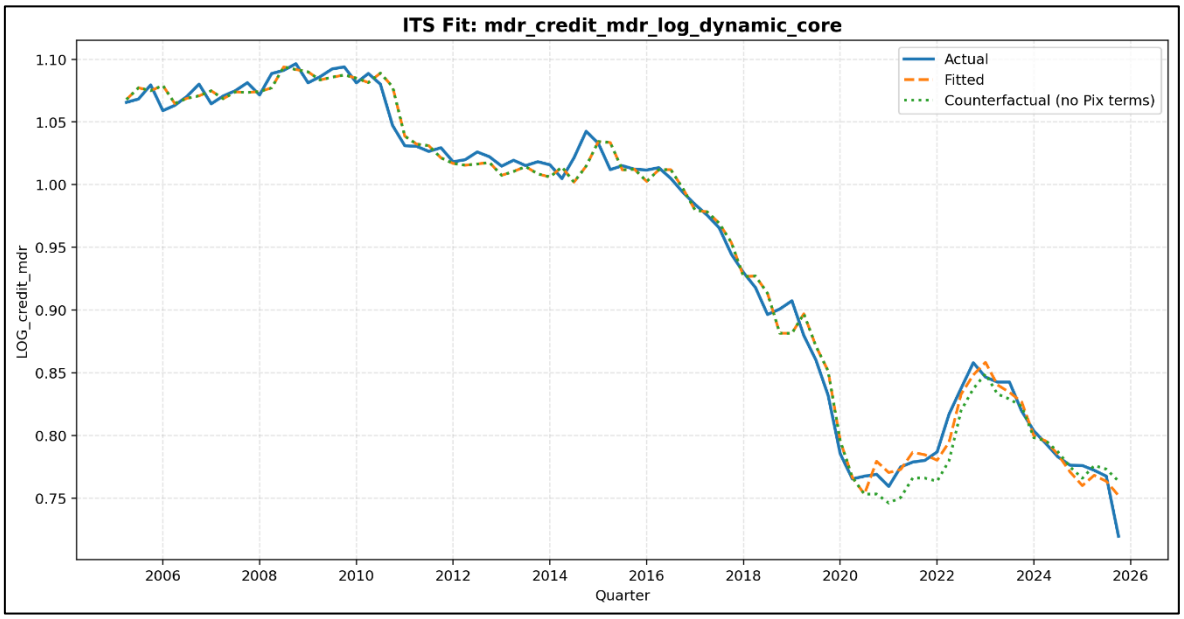
The log debit model passes RESET and stability tests but retains residual autocorrelation under the Breusch-Godfrey test. Its substantive message is nevertheless consistent with the preferred model: regulatory effects remain visible, while Pix timing does not produce a statistically reliable negative trajectory.

The log credit core equation estimates a positive and significant immediate post coefficient, corresponding to an approximate 2.8% increase, and a negative but insignificant slope. Selic is positive and significant, while Covid is negative. The model performs well on most diagnostics, with RESET close to but above the 5% threshold.

Changing the scale of the outcomes therefore does not change the principal result. Debit does not show a significant negative Pix effect, while credit continues to show a positive post-level component without a sustained slope change.



(a) Log debit MDR



(b) Log credit MDR

Figure 5.12 - Actual and fitted log MDR in the dynamic core models

Note: The solid and dashed lines report observed and one-quarter conditional fitted log MDR. The dotted comparison sets POST_PIX and TIME_AFTER_PIX to zero while retaining observed lagged level MDR and the remaining controls. Values are shown on the natural-log outcome scale and should not be read directly as MDR percentage points. The dotted paths are conditional specification comparisons, not causal counterfactuals.

5.5.4. Exposure interactions

The interaction models allow the relationship between Pix intensity and MDR to vary after launch and as the post-Pix period progresses. These specifications are theoretically attractive because competitive pressure may emerge only after Pix reaches sufficient scale. Empirically, however, they demand more independent variation than the aggregate series provides.

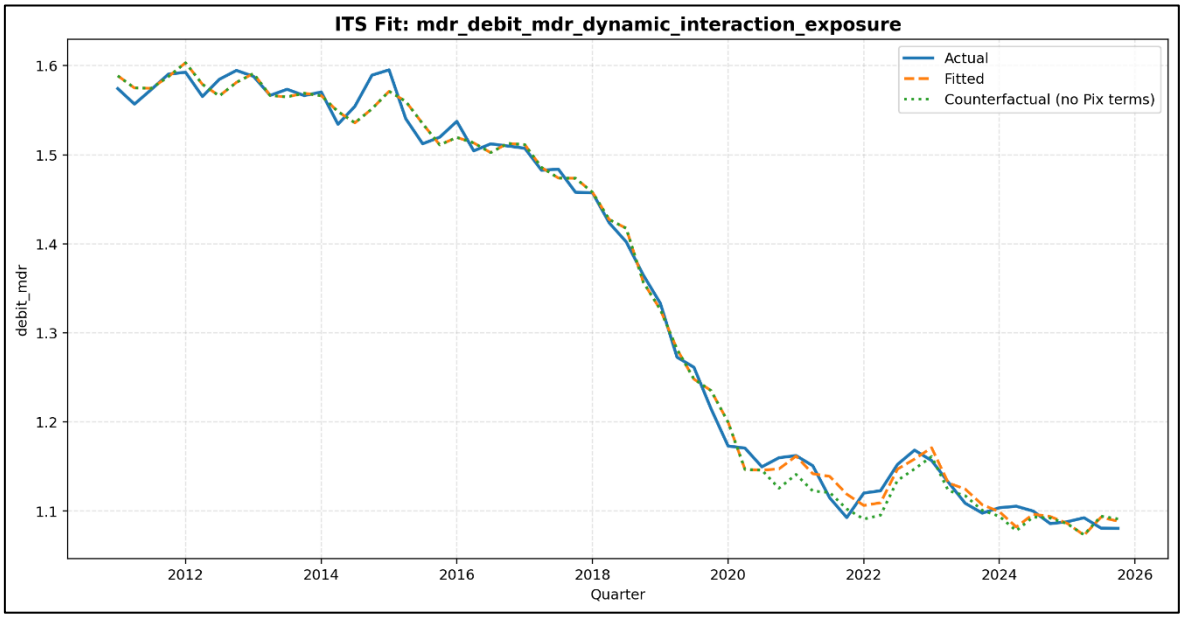
In the dynamic debit interaction equation, none of the exposure, post-time, or time-by-exposure terms is statistically significant. The immediate post coefficient is positive only at the 10% level. The 2018 cap and Q2 remain negative. The exposure-related VIF values range from very high to above one thousand, while residual autocorrelation and RESET problems remain.

The credit dynamic interaction equation produces a negative time-by-exposure coefficient at the 10% level. Considered alone, this could suggest increasing downward pressure as Pix matures. However, the main exposure effect, immediate post term, and post slope are all insignificant, and the joint post test is insignificant. An interaction coefficient cannot be interpreted separately from its main effects. Extreme multicollinearity further prevents a stable calculation of the marginal effect.

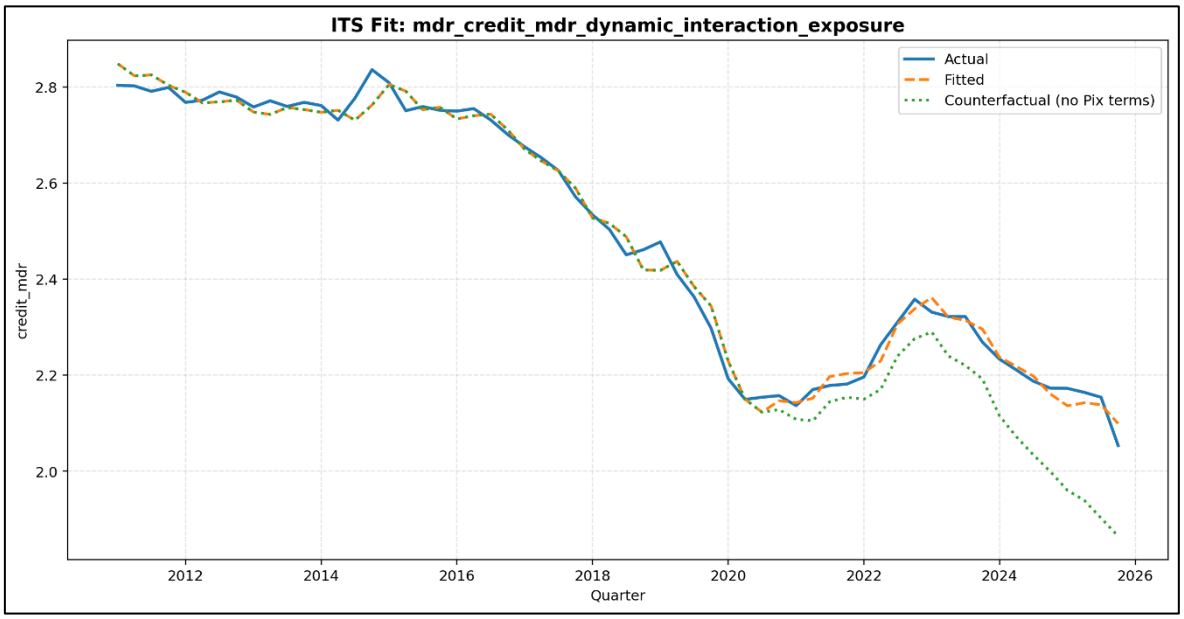
The log debit interaction model produces the most favorable exposure pattern for the competitive-pressure hypothesis. The logged Pix-to-debit ratio is negative, the post-by-exposure term is positive, and the time-by-exposure term is negative, with all three reaching conventional significance. The immediate post term is also positive and significant.

This combination is not a straightforward elasticity. The main exposure variable is logged, while the interactions use the unlogged ratio. The net association depends on the quarter, intervention status, and exposure level. In addition, the VIF values reach several thousand and the Breusch-Godfrey test rejects residual independence. The model may be detecting nonlinear exposure heterogeneity, but it may also be allocating one common post-launch trend across several nearly redundant transformations.

The corresponding credit log interaction model does not reproduce the debit pattern. None of the exposure terms is statistically significant. This lack of replication prevents the complex debit interaction result from serving as the main thesis conclusion. The interaction models are best viewed as exploratory evidence that a more granular dataset could reveal heterogeneous or nonlinear responses, not as robust estimates from the current aggregate sample.



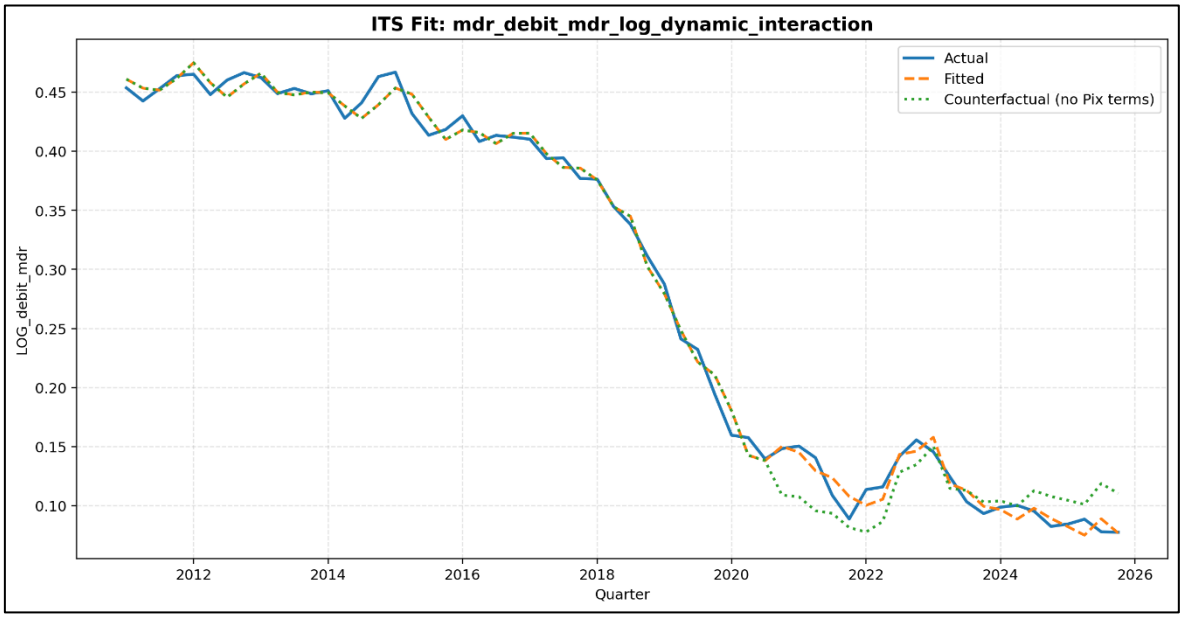
(a) Debit MDR



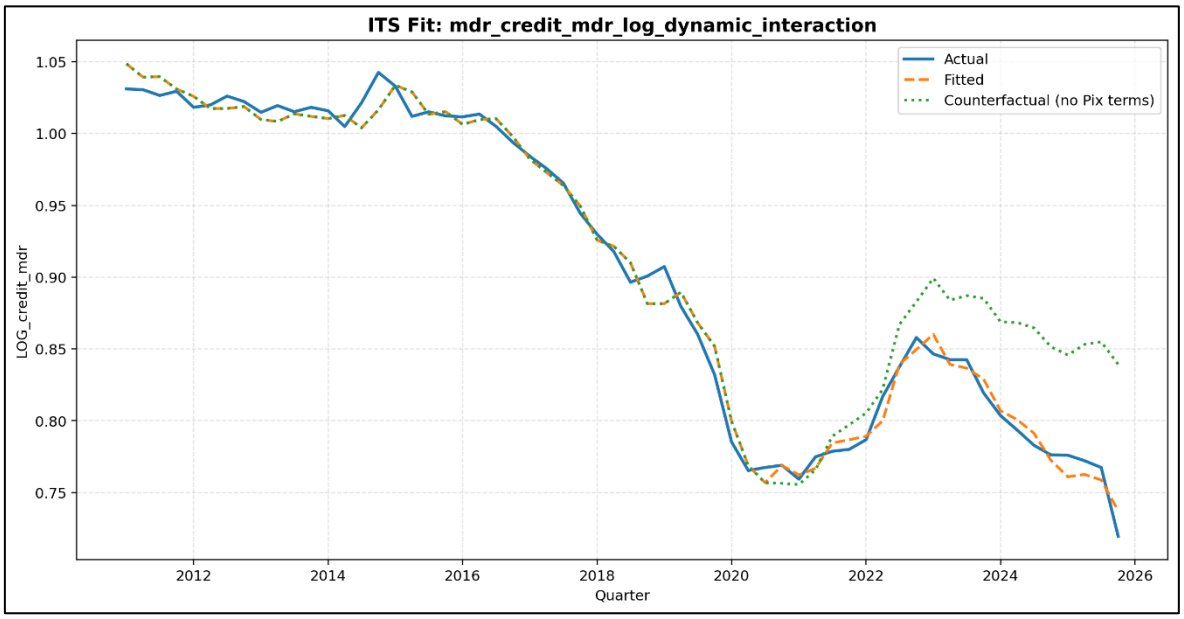
(b) Credit MDR

Figure 5.13 - Actual and fitted MDR in the dynamic exposure-interaction models

Note: The solid and dashed lines report observed and one-quarter conditional fitted MDR. In the current PNGs, the dotted line sets the base POST_PIX, TIME_AFTER_PIX, and Pix-to-debit ratio terms to zero but does not zero every constructed interaction regressor. Despite the in-figure legend, it is not a complete "no Pix terms" path. The interaction specifications also have extreme multicollinearity. The dotted line should be treated only as a partial regressor-deactivation comparison and not as a causal counterfactual. MDR is measured in percentage points.



(a) Log debit MDR



(b) Log credit MDR

Figure 5.14 - Actual and fitted log MDR in the exposure-interaction models

Note: The solid and dashed lines report observed and one-quarter conditional fitted log MDR. In the current PNGs, the dotted line does not zero LOG1P_pix_debit_ratio or all constructed exposure-interaction regressors. The in-figure "no Pix terms" label is therefore incomplete. Combined with the models' extreme multicollinearity, this means that the dotted line is only a partial regressor-deactivation comparison and must not be interpreted causally. Outcomes are displayed on the natural-log scale.

5.5.5. Alternative Pix proxies for debit MDR

The simple proxy-rotation regressions show why the hypothesis remains economically plausible despite the preferred-model results. Post-Pix time has a negative and significant association with debit MDR. Logged Pix value is also negative and significant in the short post-launch sample. Pix share has a negative and significant coefficient, while the Pix-to-debit ratio is negative but insignificant.

These estimates are not dismissed; they document a real descriptive co-movement. Debit MDR tended to be lower in periods when Pix was more mature or larger. The problem is that these equations omit lagged MDR and generally retain substantial residual persistence. The post-time model has a Durbin-Watson statistic below one and strongly non-normal residuals. The Pix-share equation also has a low Durbin-Watson statistic. The logged-Pix-value model uses only 21 observations and has a very high condition number.

The proxy coefficients are also not stable when embedded in the preferred dynamic structure. Pix share is negative in the simple equation, but the dynamic Pix-to-debit coefficient is positive and insignificant. The simple post-time slope is negative, but the preferred dynamic slope is positive and insignificant. Differencing eliminates significance, and nonlinear time produces a positive slope.

The correct interpretation is therefore that the raw data contain a negative descriptive association between Pix expansion and debit MDR, but that the association cannot be separated reliably from persistence, trend, regulation, and sample structure. This distinction allows the thesis to acknowledge what happened in the observed series without overstating what the models can identify.

5.6. Interpretation of control variables and institutional effects

5.6.1. The 2018 debit interchange cap

The most consistent non-Pix result is the negative relationship between the 2018 debit interchange cap and debit MDR. The coefficient is negative and statistically significant in the baseline debit models, preferred dynamic debit model, dynamic exposure model, nonlinear and log debit models, differenced debit models, and most simple proxy regressions.

The estimated magnitude is smaller in the dynamic models than in the static baseline. This is expected because the baseline indicator absorbs both the initial policy shift and persistent changes that subsequently remain in the MDR level. Once lagged MDR is included, the coefficient represents a more immediate conditional

adjustment. The preferred estimate is approximately -0.048 percentage points, or -4.8 basis points.

The stability of the sign across specifications gives the 2018 result greater credibility than the Pix coefficients. It is also institutionally coherent: interchange is an input into merchant acceptance costs, and the cap directly constrained debit interchange. The result does not prove complete pass-through from interchange to merchants, but it is consistent with partial transmission into MDR.

The cap's role also changes the interpretation of the Pix period. Debit MDR had already moved downward before 2020Q4, and an important part of that movement is associated with direct regulation. A model that omits or inadequately represents the 2018 policy risks attributing a continuing regulatory or market trend to Pix.

5.6.2 The revised 2023 interchange regime

The 2023 regulatory coefficient is less stable. It is negative and significant in the baseline debit model and the log debit core model, marginally negative in the preferred debit model, and insignificant in several exposure and differenced equations. In the preferred credit model, it is negative and significant, but that result is weaker in alternative credit specifications.

Several factors can explain this instability. The 2023 regime occurs entirely within the post-Pix period, when Pix adoption is already high and continuing to grow. The policy indicator is therefore correlated with post-Pix time and exposure. The available period after the regulatory change is also relatively short. Finally, the policy directly concerns debit and prepaid interchange, while the outcome equations summarize average MDR by card function. Pass-through may be gradual, incomplete, or redistributed across products.

The 2023 coefficient should consequently be treated as evidence of an additional institutional shift rather than a precisely identified policy effect. Its presence reinforces the need to avoid attributing all late post-Pix movement to competition from Pix.

5.6.2. Covid

Covid has large negative coefficients in the static level equations and the differenced transition models. In the preferred dynamic level equations, however, the coefficients become small and insignificant. This pattern indicates that Covid coincided with a substantial movement in MDR, but much of that movement persisted and is captured by lagged pricing.

The pandemic affected retail composition, merchant activity, digital adoption, risk, and the relative bargaining position of market participants. A single dummy cannot

represent all those channels. Its role is to prevent the most obvious pandemic-period discontinuity from being assigned entirely to Pix. The sensitivity of the coefficient across models also illustrates why event indicators in persistent series should not be interpreted as isolated causal parameters.

5.6.3. Selic and inflation

Macroeconomic relationships are more visible for credit than debit. In the preferred core level models, Selic and inflation are not significant. In the shorter credit exposure model and nonlinear or log credit models, Selic becomes positive and significant. In the differenced credit equations, changes in Selic and inflation are both positive and precisely estimated.

This pattern is economically plausible. Credit MDR may respond to the cost of funds, financing conditions, risk, and the value of credit services more directly than debit MDR. The differenced results suggest that short-run movements in macro-financial conditions matter even when their long-run level coefficients are difficult to separate from persistence.

For debit, macroeconomic coefficients are generally weaker and less stable. The baseline negative Selic coefficient reverses or disappears in dynamic models. This instability suggests that the baseline sign reflected omitted persistence or common trends rather than a stable structural relationship.

5.6.4. Seasonality

Seasonality is modest but relevant. Q2 repeatedly has a negative coefficient in debit MDR models, including the preferred dynamic and differenced specifications. Q1 and Q3 are usually insignificant. Credit seasonality is less stable, although Q1 is marginally negative in the preferred credit model.

These results justify retaining quarterly indicators. Even small recurring patterns can otherwise be assigned to intervention or macroeconomic variables when the post-Pix sample contains relatively few annual cycles. The seasonal coefficients are not central to the economic argument, but their inclusion improves the comparability of quarters across the long sample.

5.7. Diagnostic and model-selection assessment

The model-selection exercise demonstrates why adjusted R^2 cannot determine the preferred specification. All level models fit the MDR series extremely well because the outcomes are persistent. The static credit model, for example, explains more than 95% of variation while failing both autocorrelation and functional-form tests.

Such a model can reproduce the historical path without providing reliable inference on the intervention terms.

Adding lagged MDR produces the largest diagnostic improvement. The preferred debit model raises Durbin-Watson from below one to approximately 1.81 and removes the 5% Breusch-Godfrey rejection. The preferred credit model improves Durbin-Watson from approximately 0.57 to 1.74 and passes the main residual, heteroskedasticity, functional-form, and stability tests. Prediction errors also decline substantially.

The dynamic credit model is the strongest primary equation because it has no critical diagnostic flags. The dynamic debit model is also substantially improved, although RESET is close to the 5% threshold and the post-Pix slope has the opposite sign to the original hypothesis. The latter is an economic result rather than a statistical defect: the model is not downgraded because it fails to support the expected sign.

Exposure models face a different limitation. Their residual diagnostics can be acceptable, particularly for credit, but post-Pix time and Pix intensity are nearly redundant. Extreme VIF values imply that the model cannot allocate the shared trend reliably across those regressors. This is an identification problem within the regression design, even when residual tests are satisfactory.

Differenced models reduce this collinearity and generally improve residual behavior. Their low R^2 is not a weakness because they explain changes rather than levels. Their main contribution is negative evidence: when trend persistence is removed, Pix-related changes remain insignificant. This result is especially important for debit because it contradicts the significant negative coefficients from simpler level regressions.

Nonlinear models show that the intervention conclusion depends on the counterfactual trend. Once a quadratic trajectory is allowed, the debit slope becomes significantly positive rather than negative. Log models preserve the absence of significant negative Pix effects. Interaction models add theoretical flexibility but become too collinear for central interpretation.

The final hierarchy is therefore clear. The dynamic ITS core models provide the primary results. Differenced models provide the strongest non-stationarity check. Nonlinear and log core models assess functional form. Dynamic exposure models test the proposed intensity mechanism but receive less weight because of collinearity. Interaction-heavy and simple proxy regressions remain exploratory.

This hierarchy is not chosen because it produces a particular substantive answer. It follows from a prior methodological preference for dynamic adequacy, residual validity, interpretability, and parsimonious specification. The fact that the preferred

models do not support the original hypothesis is therefore informative rather than inconvenient. It indicates that the negative relationship visible in simpler models is not sufficiently robust to sustain a stronger claim.

Table 5.3 - Diagnostic assessment of principal MDR specifications

Model	DW	BG p-value	RESET p-value	CUSUM p-value	Assessment
Debit baseline	0.98	0.000	0.151	0.166	Material autocorrelation
Credit baseline	0.57	0.000	0.000	0.172	Autocorrelation and functional-form failure
Debit preferred dynamic	1.81	0.098	0.059	0.799	Substantially improved; RESET borderline
Credit preferred dynamic	1.74	0.416	0.552	0.998	Passes principal diagnostics
Debit dynamic exposure	1.81	0.040	0.046	0.990	Residual and severe collinearity concerns
Credit dynamic exposure	1.53	0.109	0.686	0.938	Residuals acceptable; severe collinearity

Note: BG is the Breusch–Godfrey residual-autocorrelation test. RESET evaluates functional form. CUSUM evaluates parameter stability. Exposure models also face extreme VIF values not reproduced in this compact table. Source: Author's calculations.

5.8. Main empirical findings

The first principal finding is that Pix transformed the aggregate structure of Brazilian payments. Pix value and share expanded rapidly, while the measured shares of debit and credit declined. This conclusion is strong at the descriptive level and does not depend on a particular regression. However, the share regressions do not identify direct substitution because the variables use a common denominator and Pix includes non-merchant transfers.

The second finding is that simple debit MDR models contain evidence consistent with competitive pressure. The baseline segmented model estimates a small immediate decline, and simple regressions using post-Pix time, Pix share, and logged Pix value produce negative coefficients. These results should be reported

rather than ignored because they describe the observed co-movement and explain why the hypothesis is plausible.

The third and more important finding is that the negative debit result is not robust to dynamic correction. Once lagged MDR is included, the immediate coefficient becomes positive and only marginally significant, while the post-Pix slope becomes positive and insignificant. The direct exposure coefficient is also positive and insignificant. Differenced models find no Pix effect, and the nonlinear model produces a positive post-Pix slope. The evidence therefore does not support a sustained Pix-driven decline in average debit MDR.

The fourth finding is that credit MDR shows no robust compression. The preferred model identifies a positive post-level displacement and no significant slope change. Log and nonlinear models preserve this broad pattern. Exposure terms are unstable and insignificant, while differenced equations emphasize Selic, inflation, and Covid rather than Pix. This is consistent with the weaker theoretical substitutability of credit, although the models cannot establish product differentiation as the causal explanation.

The fifth finding is that MDR persistence is economically and statistically central. The lag coefficients are large in every dynamic equation. Pricing inherited from the previous quarter explains much of current MDR, consistent with contractual and strategic adjustment frictions in acquiring markets. Ignoring this inertia materially changes the signs and significance of the intervention terms.

The sixth finding is that the 2018 debit interchange cap has the most stable negative pricing association in the analysis. Its effect remains visible across static, dynamic, differenced, nonlinear, logarithmic, and alternative-proxy debit models. This stability contrasts with the Pix coefficients and supports the interpretation that direct regulation contributed to lower debit MDR.

The overall answer to the empirical question is consequently bounded. Pix clearly created a large and credible alternative payment infrastructure and may have increased competitive pressure through channels not captured by average quarterly MDR. Merchants may have gained bargaining power, acquirers may have adjusted bundled services, or effects may differ by merchant size and sector. The available aggregate models do not show that these possible competitive mechanisms translated into a robust reduction in average debit or credit MDR during the observed period.

This conclusion should not be restated as evidence that Pix had no competitive effect. Failure to identify an average price reduction is different from demonstrating the absence of competition. Aggregate MDR can remain stable even when individual merchants receive discounts, when pricing adjustments occur through

equipment fees or settlement services, when card providers improve non-price features, or when reductions in one segment are offset by increases in another. The public data do not observe those margins.

The strongest academically defensible statement is therefore that Pix transformed payment usage, but the thesis does not find robust aggregate evidence that Pix expansion independently reduced merchant discount rates after accounting for persistence, macroeconomic conditions, Covid, seasonality, and interchange regulation. Negative associations exist in selected specifications, yet they are too sensitive to model structure to support a causal or quantitatively precise claim. This finding directly answers the research question while preserving the distinction between a plausible competitive mechanism and an empirically identified average pricing effect.

Table 5.4 - Proposition and evidence hierarchy

Proposition	Expected evidence	Result	Interpretation
Pix adoption increased rapidly	Rising value, count, and share	Supported	Large payment-system transformation
Pix directly displaced debit	Lower debit outcome without denominator bias	Not identified	Aggregate shares cannot measure one-for-one substitution
Debit MDR declined faster after Pix	Negative significant dynamic slope	Not supported	Preferred slope is positive and insignificant
Greater Pix exposure reduced debit MDR	Negative significant exposure coefficient	Not supported	Dynamic exposure is positive and insignificant
Credit responded less than debit	More negative debit pricing response	Not demonstrated	Neither preferred Pix slope is robustly negative
2018 interchange cap reduced debit MDR	Stable negative cap coefficient	Supported	Most consistent pricing result

Note: 'Not supported' refers to the preferred aggregate specifications and is not evidence that no heterogeneous or non-price competitive effect occurred. Source: Author's synthesis.

6 Discussion and Interpretation

6.1. Answering the research question

This thesis asks whether the expansion of Pix affected merchant discount rates in the Brazilian acquiring market. The evidence supports a qualified answer. Pix clearly changed the competitive environment: it became a major payment infrastructure, expanded the set of payment options available to merchants and consumers, and reduced reliance on card rails for several transaction types. The econometric results, however, do not identify a robust reduction in average debit or credit MDR attributable to Pix during the period studied.

The distinction between market transformation and price transmission is essential. Pix created an interoperable account-to-account rail with a different cost structure, settlement process, and governance model. Its adoption was sufficiently large to make it strategically relevant to banks, acquirers, fintechs, merchants, and regulators. Yet this structural change did not translate into a stable negative MDR coefficient once pricing persistence, macroeconomic conditions, Covid-19, seasonality, and interchange regulation were incorporated into the preferred specifications.

For debit MDR, simple models produce selected negative Pix-related associations, including a small immediate decline in the baseline segmented specification. These estimates are economically plausible, but they are not stable. In the preferred dynamic model, the post-Pix slope is positive and statistically insignificant. The dynamic Pix-to-debit exposure coefficient is also positive and insignificant, differenced specifications identify no negative effect, and the nonlinear model produces a positive post-Pix slope. The data therefore do not support the claim that debit MDR began declining more rapidly because of Pix.

For credit MDR, the evidence is still less consistent with fee compression. The preferred dynamic model identifies a positive post-2020 level displacement and no significant slope change. Logarithmic, nonlinear, and exposure specifications do not reveal a stable negative relationship. Credit MDR consequently provides no robust evidence of Pix-related compression.

This conclusion should not be restated as "Pix had no effect." The models observe national average MDR, not every competitive margin or merchant contract. Pix may have affected transaction routing, merchant bargaining, selective discounts, settlement conditions, service quality, or incumbent strategy without creating a sufficiently broad change in average MDR. The defensible conclusion is narrower: the available aggregate quarterly evidence does not identify an independent and robust negative effect of Pix expansion on average card MDR.

6.2. Interpreting the central empirical result

6.2.1. Payment transformation did not imply price pass-through

Pix adoption and card pricing are connected through several intermediate decisions. Pix scaled rapidly because public coordination, interoperability, mandatory participation by major institutions, continuous availability, and integration into existing banking applications reduced the network and coordination problems that often constrain new payment systems (Duarte et al., 2022). These characteristics explain why Pix could transform payment use within a short period.

MDR is governed by a broader set of forces. It reflects interchange, scheme fees, acquiring margins, risk management, settlement, merchant support, commercial negotiation, and services bundled around card acceptance. Card platforms also allocate prices and benefits across cardholders and merchants. A lower-cost alternative can therefore pressure part of the card ecosystem without producing a proportional reduction in the final fee paid by every merchant.

Pass-through depends on whether merchants can shift meaningful purchase volume, whether consumers accept steering toward Pix, how easily Pix integrates into checkout, and whether acquirers can preserve value through credit, software, equipment, fraud management, or settlement services. Incumbents may respond through selective discounts or improved bundles rather than an across-the-board MDR reduction. Aggregate fee stability is therefore compatible with increased contestability.

The large lag coefficients in the preferred models reinforces this interpretation. MDR adjusts gradually because it is embedded in contracts, pricing strategies, merchant relationships, and regulatory structures. If Pix changes negotiation conditions unevenly across firms and over time, the effect may emerge through contract renewal or merchant-specific concessions rather than a single national break. Pix transformed the environment immediately; aggregate pricing may adjust more slowly and less uniformly.

6.2.2. Why the absence of a robust negative coefficient is informative

The lack of a significant negative coefficient is not simply an unsuccessful hypothesis test. Pix had a clearly defined launch date and exceptionally rapid adoption. If it had caused a large, immediate, and broadly distributed fall in MDR, a negative level or slope change should have appeared consistently across reasonable specifications. Instead, the sign and significance of the Pix terms depend on how persistence, trend, exposure, and functional form are modeled.

This instability indicates that the simple negative association is not uniquely attributable to Pix. Debit MDR was already declining; acquiring competition and the 2018 interchange cap predated Pix; Covid-19 altered merchant activity and payment behavior; and the 2023 regime overlaps the mature Pix period. Static post-Pix variables absorb parts of these developments. Once the previous quarter's MDR and separate institutional controls are included, the estimated Pix effect weakens or changes sign.

The exposure models face a related identification problem. Pix intensity, time since launch, and the 2023 regime all rise or occur in the same short post-2020 period. Their high collinearity limits the model's ability to assign late-sample MDR movements to one factor. Differenced models remove much of the common trend and likewise fail to identify systematic Pix-related reductions in quarterly MDR changes.

The estimates do not exclude small or heterogeneous effects. Several confidence intervals remain compatible with modest declines, and national averages may conceal stronger responses in particular sectors or merchant segments. The evidence rejects a strong aggregate fee-compression narrative; it does not prove that every merchant or provider was unaffected.

6.3. Debit and credit: expected and observed asymmetry

6.3.1. Why a stronger debit effect was expected

Pix is functionally closer to debit than to credit. Both Pix and debit usually transfer funds already available to the payer, whereas credit cards combine payment execution with financing, installments, rewards, consumer protection, and liquidity management. The original expectation was therefore that Pix would place greater pressure on debit transactions and debit MDR.

The Brazilian setting strengthened this prediction. Pix can offer immediate merchant settlement and potentially lower direct acceptance costs. Merchants may

also steer consumers toward Pix where operationally feasible. These features make debit MDR the card price most likely to respond to a credible account-to-account alternative.

6.3.2. Why a robust debit response is not identified

The theoretical proximity between Pix and debit is not sufficient to determine the aggregate pricing outcome. First, substantial debit fee adjustment occurred before Pix. Antitrust intervention, the end of exclusivity arrangements, entry by acquirers and sub-acquirers, and the maquininha war had already intensified competition. The 2018 interchange cap then reduced a direct component of debit acceptance cost. By 2020, part of the available margin for broad debit MDR compression may already have been realized.

Second, Pix and debit are not operationally identical. Cards provide familiar and rapid point-of-sale routines, contactless acceptance, and integration with merchant systems. Pix may require QR initiation or a banking application and can create additional checkout friction in some settings. Substitutability consequently varies by sector, transaction size, channel, and consumer preference.

Third, national average MDR can conceal distributional effects. Pix may strengthen the position of smaller merchants that historically faced high fees, while large merchants already negotiate low rates. Concessions to relatively low-volume firms may have little influence on a transaction-weighted average. Pix could also prevent future fee increases rather than generate a visible decline, an effect the current design cannot observe because the counterfactual price path is unknown.

Finally, acquirers sell bundles rather than isolated debit transactions. Terminals, credit acceptance, settlement, reconciliation, software, accounts, and financing can preserve the commercial relationship even when Pix replaces some debit volume. Competitive response may therefore occur through equipment charges, settlement terms, service quality, or targeted rebates rather than average debit MDR.

6.3.3. Why credit MDR is more resilient

Credit remains more differentiated from Pix. Installment purchases are particularly important in Brazil, and credit cards can increase purchasing capacity and sales conversion. Rewards, chargeback rights, purchase protection, and expense consolidation further support consumer demand. Merchants may accept a higher fee because the card platform delivers benefits that an immediate account transfer does not reproduce (Rochet & Tirole, 2006, 2011).

The positive post-level coefficient in the preferred credit model should not be interpreted as evidence that Pix increased credit MDR. It shows only that the

observed post-2020 level is above the conditional model counterfactual. Changes in risk, transaction composition, installment use, merchant mix, or acquiring strategy may explain this pattern. Its relevance is that it contradicts immediate fee compression.

The credit differenced models also show stronger relationships with Selic and inflation than the debit models. This is consistent with the financing and risk components of credit-card economics. The debit-credit comparison therefore does not confirm a stronger negative Pix effect on debit, but it does show that the two MDR outcomes respond to different institutional and macro-financial forces and should not be pooled.

6.4. Interpreting the competitive mechanisms

6.4.1. Transaction substitution

Transaction substitution is the most direct route from Pix adoption to MDR pressure. If merchant purchases migrate from cards to Pix, card providers face a less secure transaction base and may reduce fees to retain volume. The aggregate payment data confirm a major compositional change, but they do not identify the amount of merchant card spending displaced.

Pix, debit, and credit shares use the same denominator, so card shares decline mechanically as Pix value expands. Total Pix value also includes person-to-person transfers, business transfers, bills, taxes, and other transactions that were never plausible card purchases. A transfer that raises total Pix value does not threaten acquiring revenue in the same way as a merchant QR payment. The broad Pix measures are therefore stronger indicators of system scale than of direct card substitution.

Measurement limits may attenuate a genuine relationship, particularly if merchant Pix adoption differs across sectors. Nevertheless, the exceptional scale of Pix means that a large and uniform merchant-substitution effect should still generate some stable aggregate pricing signal. Its absence suggests that direct purchase substitution is smaller than total Pix growth implies, that pass-through is limited, or that heterogeneous effects offset one another.

6.4.2. Merchant bargaining and incumbent adaptation

Pix can affect competition without replacing most transactions. A merchant with a credible ability to steer customers toward Pix has a stronger outside option when negotiating with an acquirer. This mechanism is likely to be heterogeneous. Large merchants may already possess bargaining power, while smaller merchants may

gain more but carry less weight in aggregate MDR. Bargaining can also improve terminal rental, settlement speed, receivables-finance charges, software, or account services without changing the reported discount rate.

The outside option is effective only when customers will follow the merchant and Pix can be integrated without excessive friction. Bargaining effects should therefore be strongest where QR or account-to-account payments are familiar and where credit or contactless convenience is less important. The national series cannot measure these merchant-specific conditions.

Incumbents can also adapt rather than compete only through price. Many banks and payment institutions participate in both Pix and the card ecosystem. They can lose card volume while gaining account activity, deposits, data, and cross-selling opportunities. Evidence that Pix can complement broader banking participation supports this interpretation (Sampaio & Ornelas, 2024). Acquirers can likewise reposition themselves as merchant-service platforms offering analytics, software, payment links, fraud management, and credit (Aurazo, 2024).

The resulting response may be improved quality, stronger bundles, or a shift in revenue sources. These changes can preserve card relevance and merchant relationships without appearing as a negative MDR coefficient. The persistence of MDR is consistent with an incumbent ecosystem that retained differentiated value while adapting to a new rail.

6.4.3. Reduced dependence and coexistence

Pix reduced the exclusivity of card infrastructure but did not eliminate the need for cards. Payment instruments specialize across use cases. Pix is strong in transfers and immediate account-funded payments; debit remains convenient for rapid in-person acceptance; and credit remains valuable for financing, installments, rewards, and protections.

Merchants can consequently become less dependent on cards while continuing to accept them. Their outside option improves, but their ability to abandon the card platform remains limited by consumer demand and product differentiation. The evidence is most consistent with movement toward a plural payment environment rather than complete substitution. Pix created a structural competitive constraint, but cards retained sufficient value to avoid uniform price compression during the sample.

6.5. Pix in the evolution of Brazilian acquiring

6.5.1. Institutional sequencing

Pix entered a market already undergoing substantial change. Historical concentration and scheme-acquirer exclusivity had been challenged by antitrust action, interoperability, new entrants, and sub-acquiring models. The maquininha war intensified competition through terminal distribution, merchant pricing, settlement, and bundled services. The counterfactual was therefore not a static high-fee market continuing unchanged after 2020.

This sequencing matters empirically. Debit MDR had a negative pre-Pix trend, and incumbents had already developed strategies for merchant segmentation and service bundling. A simple comparison of pre- and post-2020 averages risks assigning the continuation of earlier changes to Pix. The dynamic models reduce this risk by conditioning on the inherited MDR level and separating the principal regulatory regimes.

6.5.2. The 2018 interchange cap versus Pix

The stable negative coefficient associated with the 2018 debit interchange cap is one of the clearest findings of the thesis. It is consistent with Brazilian evidence reported by de Castro et al. (2023) and with international evidence that interchange regulation can lower merchant fees (Ardizzi et al., 2018).

The result illustrates the difference between direct regulation and infrastructure competition. The cap targeted a specific card cost component, creating a relatively direct transmission channel to debit MDR. Pix affects MDR indirectly through adoption, merchant substitution, bargaining, incumbent response, and contract repricing. It is therefore unsurprising that the regulatory intervention produces a clearer aggregate signal.

This comparison does not imply that fee caps are universally preferable. In two-sided markets, regulation may affect cardholder pricing, rewards, issuer revenue, and service provision. Pix also creates benefits beyond MDR, including choice, innovation, settlement speed, and resilience. The empirical conclusion is narrower: direct cost regulation is more clearly associated with debit fee compression than the indirect competitive pressure of Pix in the available data.

6.5.3. Pix as a distinct competitive shock

Earlier acquiring competition largely involved firms offering access to the same card schemes. Pix introduced a separate account-to-account infrastructure. It therefore

changed the merchant's technological option, not merely the number of suppliers within the incumbent architecture.

Infrastructure competition may operate more slowly than within-card competition. It requires changes in consumer habits, checkout design, merchant integration, and product functionality. Its effects may emerge through business-model adaptation rather than rapid fee cuts. Moreover, major banks participate in Pix while retaining card and acquiring businesses, which creates incentives to manage channel substitution across a broader customer relationship.

Pix should therefore not be judged as unsuccessful because average MDR did not fall robustly. It succeeded in creating a widely used alternative infrastructure. What remains unsupported is the specific claim that this achievement independently reduced average card MDR during the observed period.

6.6. Pix and the European payment ecosystem

The European comparison helps separate the existence of instant-payment infrastructure from its use as a merchant-facing competitor to cards. Europe has developed instant euro payments through the SEPA Instant Credit Transfer (SCT Inst) scheme and settlement infrastructures such as the Eurosystem's TARGET Instant Payment Settlement (TIPS). Like Pix, this architecture supports account-to-account transfers in seconds and continuous operation. Regulation (EU) 2024/886 has strengthened reachability by requiring payment service providers that offer ordinary euro credit transfers also to offer instant transfers, subject to a phased implementation timetable, and by preventing providers from charging more for an instant transfer than for a corresponding ordinary credit transfer (European Central Bank, n.d.; European Parliament & Council of the European Union, 2024).

The governance and adoption paths nevertheless differ. Pix was introduced as a nationally coordinated system under the Banco Central do Brasil, with common rules, a central alias directory, standardized user experiences, QR functionality, a recognizable brand, and mandatory participation by major institutions. These features allowed the payment rail, addressing layer, and consumer proposition to scale together (Duarte et al., 2022). The European ecosystem instead combines EU legislation, the European Payments Council's scheme rules, Eurosystem and private clearing infrastructures, and payment products offered by many national banking markets. SEPA created common technical reach, but merchant acceptance and the consumer-facing proposition have remained more dispersed across providers and countries.

This difference is economically important. Technical availability does not by itself make an instant transfer a close substitute for a card at the point of sale. The

competitive effect also depends on merchant interfaces, QR or request-to-pay functionality, refunds, fraud allocation, consumer protection, checkout speed, reconciliation, and the incentives facing banks and payment providers. Pix is therefore an informative European case not because its outcomes can be transferred mechanically, but because it shows what can occur when interoperability, broad reach, low user friction, and merchant usability are developed as parts of the same public-infrastructure strategy.

The Brazilian evidence also provides a caution for European policy. Pix achieved exceptional scale and clearly reduced the exclusivity of card rails, yet this thesis does not identify a robust independent fall in average card MDR. Europe should therefore distinguish at least three stages: infrastructure reachability, use in merchant transactions, and pass-through into incumbent acceptance prices. Progress at the first stage may improve resilience, choice, and innovation without automatically producing the third. An empirical evaluation of European instant payments should consequently use merchant-payment volumes and merchant acceptance costs, rather than total instant-transfer volume alone.

A simple comparison illustrates both the potential cost advantage and the limits of available figures. Duarte et al. (2022) report an early average Pix cost to merchants of approximately 0.22 per cent of transaction value. As an internal card benchmark, the post-Pix observations in this thesis have average debit and credit MDR of approximately 1.12 and 2.22 per cent, respectively. These figures are consistent with a sizeable direct acceptance-cost gap, but they are not evidence that every Pix transaction replaced a card purchase or that the gap was passed through into lower card MDR.

Table 6.1 - Cost comparison between European and Brazilian instant payments systems

Cost Layer	Brazil	European Union	Interpretation
Consumer instant transfer	Pix is generally free for individuals when used outside commercial situations.	The price of an instant euro transfer may not exceed the price of the corresponding ordinary credit transfer under Regulation (EU) 2024/886.	These are user-pricing rules, not merchant acceptance costs.
Instant-payment infrastructure	Pix is operated as public infrastructure, while participants and merchant providers may face or set service charges.	TIPS charges EUR 0.002 per settled instant payment, split between the sending and receiving participants (European Central Bank, n.d.).	The TIPS tariff is a wholesale settlement price and should not be compared directly with MDR.
Merchant/card benchmark	Early evidence places average Pix merchant cost near 0.22 per cent; this thesis observes post-Pix mean MDR near 1.12 per cent for debit and 2.22 per cent for credit.	Consumer-card interchange is capped at 0.2 per cent for debit and 0.3 per cent for credit under Regulation (EU) 2015/751.	European interchange is only one component of the merchant service charge; it is not the merchant's total card cost.

Note: The table deliberately avoids converting EUR to BRL. Currency conversion would create a false comparison because the EUR 0.002 TIPS figure is a per-transaction wholesale settlement tariff, whereas the Brazilian percentage figures are merchant-facing charges. Retain the qualification directly below the table.

No single harmonized European merchant price for instant account-to-account acceptance is available. Provider charges, integration costs, and overlay services vary, just as commercial Pix pricing varies across Brazilian institutions. The defensible comparison is therefore structural rather than a claim that one continent has a single lower price. Both systems can settle account-to-account payments at very low infrastructure cost, but the amount ultimately paid by a merchant depends on the competitive and service layer above the rail. This reinforces the thesis's central result: a low-cost public rail can create contestability, while transmission to incumbent merchant prices remains an empirical question.

6.7. Contribution to the literature

The first contribution is to distinguish fast-payment adoption from incumbent pricing. The Brazilian evidence confirms that coordinated public infrastructure can achieve rapid diffusion and transform payment behavior. It also shows that adoption does not guarantee immediate pass-through into an incumbent merchant price. Merchant integration, product substitutability, contracts, and market structure determine whether contestability becomes observable fee compression.

The second contribution concerns two-sided market theory. Comparing Pix's direct cost with MDR is insufficient because cards offer consumer-side benefits that can increase merchants' willingness to accept them. Credit, rewards, protections, and convenience differentiate the platform; debit also retains advantages through established point-of-sale integration. Infrastructure cost differences therefore do not map mechanically into final merchant prices (Rochet & Tirole, 2006, 2011).

The third contribution concerns public digital infrastructure and competition policy. Pix demonstrates that public infrastructure can expand access, interoperability, and choice even when a specific incumbent price remains persistent. Its success should be assessed across several outcomes rather than inferred from MDR alone. Conversely, claims that infrastructure will reduce incumbent fees should be tested rather than assumed.

The closest thesis-level benchmark is Oliveira (2025), which also investigates the relationship between Pix and merchant discount rates in Brazil. The overlap is useful because it shows that the present thesis is not introducing the Pix-MDR question in isolation. It instead revisits the same core relationship with a different empirical emphasis. Oliveira provides the direct prior benchmark, whereas this thesis gives greater weight to source-unit validation, explicit separation of the 2018 and 2023 interchange regimes, lagged MDR persistence, differenced and nonlinear specifications, alternative Pix-exposure measures, and a formal diagnostic and model-selection sequence.

The comparison also clarifies why the contribution is substantive rather than a change in wording. In the simpler specifications estimated here, selected Pix coefficients are negative, so an interpretation of fee pressure is empirically plausible under a parsimonious design. Those negative associations do not remain stable once inherited MDR dynamics, pre-existing trends, overlapping regulation, and alternative functional forms are considered. Relative to Oliveira (2025), the present thesis therefore places a higher evidential threshold on attributing average MDR movements to Pix and reaches a more bounded conclusion: Pix clearly transformed the competitive environment, but a robust independent reduction in national average debit or credit MDR is not identified. The studies should be read as

complementary stages in a developing literature, with the difference centered on specification breadth, diagnostics, and the scope of inference rather than on the importance of Pix itself.

6.8. Managerial implications

For acquirers and merchant-service providers, stable aggregate MDR should not be interpreted as insulation from Pix. Merchants now have another route for immediate electronic payment, reducing the exclusivity of card acceptance. The strategic response should focus on services that Pix alone does not provide: integrated acceptance, reconciliation, fraud management, analytics, software, settlement, and working-capital solutions. Pricing should also become more segmented because merchants differ in Pix adoption, credit dependence, and demand for bundled services.

Banks and issuers should evaluate Pix and cards at the customer-relationship level. Credit remains differentiated through financing, installments, rewards, and protections, but dependence on interchange and merchant revenue becomes riskier as public infrastructure and regulatory scrutiny expand. Pix can simultaneously reduce card revenue and deepen account engagement, deposits, data generation, and cross-selling. The stronger short-run macroeconomic relationships in the credit models also indicate that payment competition must be separated from funding-cost and credit-risk effects.

For fintechs, access to the public rail lowers infrastructure barriers but does not guarantee a sustainable merchant proposition. Competitive advantage is more likely to come from sector-specific interfaces, reconciliation, fraud prevention, embedded acceptance, support, and cash-flow services than from low transaction cost alone. Aggregate MDR stability may conceal opportunities among smaller or underserved merchants.

Merchants should compare the total value of payment methods rather than MDR alone. Settlement timing, fraud risk, refunds, consumer preference, checkout speed, installment demand, and system integration all affect the optimal payment mix. Pix can strengthen negotiation where merchants can credibly steer volume, but abandoning cards is unlikely to be optimal for firms that rely on consumer credit or contactless convenience. A portfolio strategy can use Pix as an outside option while retaining differentiated card functions.

6.9. Policy implications

Pix should be evaluated through adoption, access, interoperability, settlement, resilience, innovation, merchant choice, and competitive response. Average MDR is relevant but incomplete. The results caution against assuming that rapid adoption automatically disciplines every incumbent price. If fee pass-through is a policy objective, merchant usability, effective steering, competitive service provision, and transparency around bundled charges also matter.

Competition authorities should monitor the full merchant-service package. Pressure may appear in terminal charges, settlement conditions, receivables finance, software, or service quality rather than MDR. Aggregate averages may also conceal selective concessions or unequal pass-through between large and small merchants. Distributional data are therefore important for assessing market power.

The comparison between Pix and the 2018 cap clarifies the role of policy instruments. Public infrastructure is well suited to expanding choice, entry, innovation, and resilience. Targeted regulation can affect a specific cost component more directly, although it may redistribute costs within a two-sided platform. The instruments are complementary rather than interchangeable and should be matched to the policy objective.

The principal data limitation also implies a concrete policy recommendation. Regulators should publish anonymized merchant Pix receipts by sector and size, MDR distributions rather than only averages, provider-level aggregates, settlement conditions, and broader merchant-service costs. These data would permit stronger evaluation of whether Pix effects are concentrated among particular merchants, industries, regions, or providers.

Internationally, Brazil demonstrates that strong governance and interoperability can produce rapid fast-payment adoption. It also shows that payment-system transformation and incumbent-price effects are separate stages. Other jurisdictions should evaluate infrastructure availability, consumer and merchant adoption, transaction substitution, provider response, and final-price pass-through independently rather than treating progress in one stage as proof of the next.

6.10. Limits of interpretation

6.10.1. Aggregation and measurement

The analysis uses national quarterly averages. It cannot observe merchant contracts, provider strategy, or transaction-level payment choice. Average MDR may remain stable while fees fall for some merchants and rise for others. Effects may differ by merchant size, sector, region, channel, risk profile, or acquirer.

Pix exposure is measured broadly because the available value series combines merchant payments with P2P, business, bill, tax, and other transfers. The resulting Pix, debit, and credit variables are referred to as shares for convenience, but they are shares of the thesis's constructed payment-value total rather than strict market shares of directly substitutable transactions. A P2P transfer can raise Pix share and mechanically lower card share without displacing a card purchase. Broad Pix value can therefore exaggerate apparent substitution in the composition equations while adding measurement noise to the MDR equations. The measures establish system scale and relative composition more reliably than merchant-specific competitive exposure.

The thesis can therefore conclude that a Pix effect is not robustly visible in national average MDR. It cannot conclude that no merchant experienced stronger bargaining power or fee pressure.

6.10.2. Identification and overlapping events

Pix was introduced nationally, so there is no untreated Brazilian control group. Interrupted time-series models construct the counterfactual from the pre-Pix path and observed controls. Covid-19, changes in competition, monetary conditions, fraud, product innovation, and merchant composition may still affect post-2020 coefficients.

The regulatory indicators and Pix variables also overlap in time. The effects of the 2018 cap may persist, while the 2023 regime occurs during advanced Pix adoption. Pix intensity and post-Pix time are highly correlated, producing unstable exposure and interaction coefficients. These constraints justify the thesis's emphasis on conditional associations and robustness rather than definitive causal attribution.

6.10.3. Time horizon and outcome coverage

The sample contains approximately five years after Pix launch but a shorter period after mature adoption and the 2023 regime. Contractual and business-model adjustment may take longer. The analysis therefore evaluates the first phase of Pix diffusion, not the final equilibrium of Brazilian payments.

MDR is also only one dimension of competition. Terminal fees, settlement, receivables anticipation, software, financing, fraud services, and quality may change independently. A stable MDR can coexist with lower total merchant cost or better services, just as a lower MDR can be offset by other charges.

6.10.4. Model uncertainty

Static, dynamic, differenced, nonlinear, logarithmic, and interaction models answer related but not identical questions. Their changing signs demonstrate that the data do not support a uniquely determined Pix effect. The preferred dynamic models are prioritized because they improve diagnostics and reflect pricing persistence, but lagged outcomes can absorb slow-moving effects and the high persistence of credit MDR complicates long-run interpretation.

The conclusion therefore rests on triangulation. No single specification proves the result. Rather, a negative Pix effect fails to remain stable across the models that address the principal statistical risks. This supports cautious non-confirmation, not proof of zero effect.

6.11. Discussion summary

The evidence supports five conclusions. First, Pix structurally transformed Brazilian payments and created a credible alternative to card rails. Second, this transformation did not produce a robustly identified reduction in average debit or credit MDR during the observed period. Third, competition may still operate through merchant bargaining, selective pricing, service quality, transaction routing, and incumbent adaptation. Fourth, the Brazilian institutional sequence is decisive: acquiring competition and direct interchange regulation preceded Pix, and the 2018 cap provides the clearest debit pricing result. Fifth, public infrastructure affects private pricing conditionally rather than mechanically; pass-through depends on substitutability, integration, platform economics, and market heterogeneity.

The central interpretation is therefore precise. Pix transformed the competitive environment of Brazilian payments, but the available aggregate evidence does not demonstrate that it independently reduced average merchant discount rates. This conclusion preserves Pix's strategic and policy importance while matching the strength of the claim to the identification capacity of the data. Chapter 7 draws these findings together and states the final contribution, limitations, and research agenda.

7 Conclusion

7.1. Summary of the thesis

This thesis examined whether the expansion of Pix affected merchant discount rates in the Brazilian acquiring market. The research question was motivated by a clear economic proposition. Pix introduced a widely accessible, interoperable, and generally low-cost account-to-account payment infrastructure into a market in which merchants had historically depended heavily on card acceptance. By enabling immediate settlement outside the traditional card chain, Pix could reduce transaction dependence on card rails, improve merchants' outside options, and place competitive pressure on the pricing of incumbent acquirers. Merchant discount rates offered a relevant observable outcome through which to test whether this pressure translated into lower card acceptance costs.

The Brazilian setting made the question especially important but also empirically demanding. Pix was introduced nationally rather than through a staggered or regional rollout, leaving no natural untreated domestic comparison group. It also entered a payment market that was already changing. The Brazilian acquiring sector had experienced the end of exclusivity arrangements, entry by new acquirers and sub-acquirers, intensified competition associated with the maquininha war, and direct regulation of debit interchange. The Covid-19 shock and substantial variation in monetary conditions further overlapped the post-Pix period. A credible analysis therefore required more than comparing average MDR before and after November 2020.

To address this problem, the thesis constructed a quarterly master dataset combining payment values, transaction counts, debit and credit MDR, Pix adoption measures, macroeconomic controls, seasonality, and regulatory indicators. Particular attention was given to source-unit validation and consistent quarterly construction. The empirical design then followed a staged model sequence. Payment-composition regressions examined how Pix expansion coincided with debit and credit shares. Segmented interrupted time-series models estimated immediate and trend changes around the launch of Pix. Dynamic specifications added lagged MDR to account for pricing persistence. Differenced equations tested sensitivity to common trends and non-stationarity. Nonlinear, logarithmic,

interaction, and alternative-exposure models evaluated the robustness of the main conclusions.

The payment-composition analysis confirmed that Pix became a major component of the Brazilian payment system and that measured debit and credit shares declined as Pix expanded. This result demonstrates a profound reweighting of the aggregate payment mix. It does not, however, identify the amount of direct card substitution. Pix and card shares are constructed from the same denominator, and total Pix value includes transfers and other use cases that do not compete directly with merchant card purchases. The composition results therefore establish system transformation rather than one-for-one transaction displacement.

The MDR models produced a more cautious conclusion. Several simple debit specifications displayed negative Pix-related associations. The baseline segmented model estimated a small immediate decline in debit MDR, and simpler regressions using post-Pix time, Pix share, and logged Pix value also produced negative coefficients. These estimates are consistent with the initial competitive-pressure hypothesis at a descriptive level.

The negative relationship was not robust when the statistical structure of MDR was modeled more fully. Debit and credit MDR were highly persistent. Once lagged MDR was included, the preferred debit model no longer showed a negative immediate or slope effect attributable to Pix. The post-Pix slope was positive and statistically insignificant, and the dynamic Pix-to-debit exposure coefficient was also positive and insignificant. Differenced models did not identify a negative Pix effect, while the nonlinear debit model produced a positive post-Pix slope. The direction and significance of the Pix terms therefore depended materially on specification.

The credit results provided even less evidence of fee compression. The preferred dynamic model identified a positive post-2020 level displacement and no significant slope change. Logarithmic and nonlinear specifications preserved the absence of a negative credit trajectory. Exposure effects were unstable and statistically weak. These findings are consistent with the stronger functional differentiation of credit cards, particularly their financing, installment, reward, and consumer-protection functions, but the aggregate design cannot directly identify those mechanisms.

The most stable pricing result concerned the 2018 debit interchange cap. Its coefficient was negative and statistically significant across the preferred debit model and a broad range of robustness specifications. This finding is institutionally coherent because interchange is a direct component of card acceptance costs. It also demonstrates why the pre-Pix regulatory history must be incorporated into any interpretation of debit MDR. Part of the fee compression visible before and around

the rise of Pix is more consistently associated with direct regulation than with the later expansion of instant payments.

The thesis consequently distinguishes between the competitive significance of Pix and an identified average price effect. Pix transformed the payment environment, reduced the exclusivity of card rails, and created a credible alternative for merchants and consumers. The available aggregate evidence does not demonstrate that this transformation independently reduced average debit or credit MDR during the period studied. Competitive responses may have occurred through merchant-specific negotiation, service bundling, settlement conditions, product quality, or strategic adaptation without producing a uniform decline in the national MDR series.

7.2. Main contribution

The first contribution of this thesis is to shift the analysis of Pix from adoption and financial inclusion toward incumbent pricing and market structure. Much of the existing discussion rightly emphasizes the exceptional diffusion of Pix, its public-infrastructure design, and its role in expanding access to fast digital payments. This thesis asks a different second-stage question: whether the new infrastructure altered the merchant pricing of the incumbent card ecosystem.

This distinction is important because adoption is not equivalent to competitive pass-through. A payment system can become widely used and strategically important without producing an immediate reduction in the average price of a differentiated incumbent service. The results show that the relationship between public infrastructure and private pricing is mediated by merchant behavior, consumer preferences, platform economics, regulation, contractual inertia, and incumbent adaptation.

The second contribution is methodological. The analysis demonstrates that conclusions about the Pix-MDR relationship are sensitive to the treatment of persistence, trend, exposure, and regulation. Simple post-launch or level regressions can produce negative and apparently precise Pix coefficients. Those results weaken or reverse when lagged MDR, differencing, nonlinear trends, and separate regulatory indicators are introduced. The thesis therefore contributes a diagnostics-governed model sequence rather than relying on a single preferred regression selected by statistical significance.

The third contribution is the explicit separation of Pix from the 2018 debit interchange cap and the revised 2023 interchange regime. This institutional distinction changes the interpretation of the MDR series. The stable negative debit-cap coefficient provides stronger evidence of pricing transmission than the Pix

terms. The result indicates that direct cost regulation and infrastructure-based competition are different mechanisms and should not be combined into a single post-2020 narrative.

The fourth contribution is conceptual. The thesis shows why the absence of an aggregate MDR decline should not be interpreted as evidence that Pix lacked competitive importance. MDR is one merchant-facing price within a wider acquiring relationship. Competition can affect terminal charges, settlement, receivables finance, software, service quality, selective discounts, and merchant bargaining. Aggregate price stability can coexist with meaningful structural change and heterogeneous competitive responses.

The final contribution is a more bounded and reproducible answer to the research question. Rather than assigning a precise causal reduction to Pix, the thesis identifies which claims are supported, which are descriptive, and which remain unverified. Pix adoption and payment-system transformation are strongly supported. Direct debit-specific substitution is not identified by the common-denominator share models. A robust Pix-driven reduction in debit or credit MDR is not supported by the preferred specifications. The regulatory contribution to debit MDR is more stable. This hierarchy aligns the thesis's conclusions with the actual identification capacity of the data.

7.3. Final answer to the research question

The expansion of Pix affected the competitive environment of the Brazilian acquiring market by creating a rapidly adopted, low-cost, and interoperable alternative to card-based payment acceptance; however, the empirical analysis does not find robust evidence that this change independently reduced average debit or credit merchant discount rates during the observed period. Negative Pix-related associations appear in simpler debit models, but they do not survive consistent treatment of MDR persistence, pre-existing trends, interchange regulation, macroeconomic conditions, and alternative functional forms. The preferred debit and credit models identify no sustained negative post-Pix slope, while the 2018 debit interchange cap has a more stable negative relationship with debit MDR. The thesis therefore concludes that Pix transformed payment choice and plausibly increased contestability, but that aggregate pass-through into lower card acceptance prices is not demonstrated by the available data.

7.4. Limitations

The conclusions are limited by the use of national aggregate data. The analysis cannot observe merchant-level contracts, acquirer pricing strategies, sectoral differences, or variation by merchant size. A national average may conceal meaningful fee reductions for some merchants and offsetting movements for others. The results therefore apply to aggregate MDR and cannot be generalized to every merchant or provider.

The nationwide launch of Pix prevents the construction of a natural untreated Brazilian control group. Interrupted time-series methods estimate a counterfactual from the pre-Pix path and observed controls, but they cannot eliminate every concurrent shock. Covid, changes in competition, monetary conditions, fraud, product innovation, and merchant composition may still influence post-2020 coefficients.

Pix exposure is also measured imperfectly. Total Pix value includes P2P, merchant, business, bill, tax, and other transfers, whereas card values predominantly represent purchases. The Pix, debit, and credit "shares" are consequently descriptive shares of a broad constructed denominator, not strict market shares among fully substitutable products. P2P growth can mechanically reduce measured card shares without reducing card purchases, and it can weaken the connection between broad Pix exposure and MDR. These variables are therefore used as indicators of system scale and competitive exposure, not as direct measures of merchant substitution. Separating person-to-business Pix receipts from transfers would be necessary to estimate the card-replacing channel more precisely.

The post-intervention period remains limited relative to the time required for contracts and business models to adjust. The thesis evaluates the first phase of Pix diffusion rather than the final long-run equilibrium of the Brazilian payment market. Finally, MDR does not capture every dimension of merchant cost or competition. Pricing changes may occur through settlement, equipment, software, financing, or service bundling instead of the transaction discount rate itself.

7.5. Future research

The most important extension is the use of merchant-level data. Contractual MDR observations linked to merchant size, sector, region, transaction volume, and payment mix would reveal whether Pix effects are concentrated in particular segments. Such data would allow researchers to distinguish a genuinely absent effect from an aggregate average that conceals heterogeneous responses.

Acquirer-level panel data would provide a second major improvement. Different acquirers vary in bank affiliation, merchant portfolio, geographic presence, pricing strategy, digital capability, and exposure to small businesses. A provider panel could examine whether firms facing greater Pix competition reduced MDR, changed settlement terms, or shifted revenue toward other merchant services. It could also reveal whether incumbent and challenger responses differed.

Future work should prioritize merchant-specific Pix transaction data. Separating person-to-business and business-to-business receipts from transfers would produce a more economically relevant exposure measure. Matching merchant Pix receipts with card values would permit direct estimation of whether card transaction volume, rather than merely card share, changes as Pix adoption increases.

Sectoral analysis is also necessary. Pix may be highly substitutable for debit in restaurants, professional services, informal retail, and low-ticket commerce, while cards may remain more resilient in supermarkets, travel, e-commerce, and installment-intensive sectors. Sector-level estimates could connect payment functionality to competitive response more directly than a national aggregate model.

Regional variation may offer an additional identification strategy. Differences in banking access, smartphone adoption, merchant formality, income, and initial card use could generate variation in the timing or intensity of merchant Pix adoption. A regional panel with appropriate controls could move closer to a treated-comparison design, although exposure would still need to be interpreted carefully.

Cross-country research could assess whether the Brazilian result is specific to its institutional environment. Comparative studies should distinguish systems by public or private governance, participation rules, merchant pricing, interoperability, point-of-sale integration, and the pre-existing competitiveness of card acquiring. A fast payment system introduced into a less competitive card market may produce a different pricing response from Pix in Brazil.

The analysis should also be updated as the post-Pix period lengthens. Additional observations will improve the ability to distinguish long-run changes from temporary post-launch dynamics and from the 2023 regulatory regime. Longer samples can test whether pricing effects emerge gradually through contract renewal and strategic adaptation rather than as an immediate break.

New Pix functionalities create a further research agenda. Pix Automático entered operation on June 16, 2025 and may compete with card-based recurring payments and direct-debit arrangements in ways that differ from the original transfer and purchase use cases (Banco Central do Brasil, 2025). The available post-launch window is still too short for credible evaluation, so its effects should be studied as

observations accumulate. Any guaranteed or credit-linked Pix functionality should likewise be treated as a distinct institutional development and classified according to its operational status at the time of analysis.

Finally, future research should broaden the definition of competitive outcome beyond MDR. Total merchant payment cost, terminal charges, settlement speed, receivables-anticipation pricing, software fees, service quality, and merchant switching should be analyzed jointly. This would provide a more complete assessment of whether public payment infrastructure changes the economics of incumbent merchant services even when average transaction fees remain stable.

The central question will therefore remain relevant as Pix and the acquiring market continue to evolve. This thesis establishes a cautious empirical benchmark: the initial expansion of Pix transformed Brazilian payments but did not produce a robustly identified reduction in aggregate card MDR. More granular data, longer time horizons, and stronger comparative designs are required to determine where, when, and through which mechanisms infrastructure competition ultimately reaches merchant prices.

Bibliography

[1] G. Ardizzi, A. Nobili, and G. Rocco, "The impact of the interchange fee regulation on merchants: Evidence from Italy," Questioni di Economia e Finanza No. 434, Banca d'Italia, 2018. [Online]. Available: https://www.bancaditalia.it/pubblicazioni/qef/2018-0434/

[2] M. Armstrong, "Competition in two-sided markets," The RAND Journal of Economics, vol. 37, no. 3, pp. 668–691, 2006. doi: 10.1111/j.1756-2171.2006.tb00037.x

[3] J. Aurazo, "Interchange fees, access pricing and sub-acquirers in payment markets," BIS Working Papers No. 1163, Bank for International Settlements, 2024. [Online]. Available: https://www.bis.org/publ/work1163.htm

[4] Banco Central do Brasil, Circular No. 3,887, of March 26, 2018, Brasília: Banco Central do Brasil, 2018.

[5] Banco Central do Brasil, "Banco Central aprimora regulação da tarifa de intercâmbio (TIC)," 2022. [Online]. Available: https://www.bcb.gov.br/detalhenoticia/633/noticia

[6] Banco Central do Brasil, Relatório de Gestão do Pix: Concepção e primeiros anos de funcionamento (2020–2022), Brasília: Banco Central do Brasil, 2023. [Online]. Available: https://www.bcb.gov.br/content/estabilidadefinanceira/pix/relatorio_de_gestao_pix/relatorio_gestao_pix_2023.pdf

[7] Banco Central do Brasil, "Pix Automático," 2025. [Online]. Available: https://www.bcb.gov.br/meubc/faqs/p/pix-automatico

[8] Banco Central do Brasil, "Pix em números," [Online]. Available: https://www.bcb.gov.br/estabilidadefinanceira/pix-em-numeros-estatisticas. [Accessed: Jun. 10, 2026].

[9] Bank for International Settlements, Faster Digital Payments: Global and Regional Perspectives, BIS Papers No. 152, Basel: Bank for International Settlements, 2024. [Online]. Available: https://www.bis.org/publ/bppdf/bispap152.htm

[10] Brazil, Lei No. 13.455, de 26 de junho de 2017, Brasília, 2017. [Online]. Available: https://www.planalto.gov.br/ccivil_03/_ato2015-2018/2017/lei/l13455.htm

[11] Committee on Payments and Market Infrastructures, Developments in Retail Fast Payments and Implications for RTGS Systems, CPMI Papers No. 201, Bank for International Settlements, 2021. [Online]. Available: https://www.bis.org/cpmi/publ/d201.htm

[12] Conselho Administrativo de Defesa Econômica, "CADE signs agreement with Itaú, Rede and Hipercard to stimulate competition in the market for electronic means of payment," 2017. [Online]. Available: https://www.gov.br/cade/en/matters/news/cade-signs-agreement-with-itau-rede-and-hipercard-to-stimulate-the-competition-in-the-market-of-electronic-means-of-payment

[13] Conselho Administrativo de Defesa Econômica, "CADE celebrates agreements to stimulate competition in electronic means of payment," 2017.

[14] Conselho Administrativo de Defesa Econômica, "CADE clears increase of Bradesco and Banco do Brasil's stake in Cielo," 2025.

[15] D. T. de Castro, E. E. Schmitz, and M. de A. Azevedo, "An empirical analysis of debit card interchange fee regulation: Evidence from Brazil," Latin American Journal of Central Banking, vol. 4, no. 1, 2023.

[16] A. Duarte, J. Frost, L. Gambacorta, P. Koo Wilkens, and H. S. Shin, "Central banks, the monetary system and public payment infrastructures: Lessons from Brazil's Pix," BIS Bulletin No. 52, Bank for International Settlements, 2022. [Online]. Available: https://www.bis.org/publ/bisbull52.htm

[17] D. S. Evans and R. Schmalensee, "The industrial organization of markets with two-sided platforms," Competition Policy International, vol. 3, no. 1, pp. 151–179, 2007.

[18] M. L. Katz and C. Shapiro, "Network externalities, competition, and compatibility," American Economic Review, vol. 75, no. 3, pp. 424–440, 1985.

[19] A. Linden, "Conducting interrupted time-series analysis for single- and multiple-group comparisons," The Stata Journal, vol. 15, no. 2, pp. 480–500, 2015. doi: 10.1177/1536867X1501500208

[20] J. Lopez Bernal, S. Soumerai, and A. Gasparrini, "A methodological framework for model selection in interrupted time series studies," Journal of Clinical Epidemiology, vol. 103, pp. 82–91, 2018. doi: 10.1016/j.jclinepi.2018.08.009

[21] J. McAndrews and Z. Wang, "The economics of two-sided payment card markets: Pricing, adoption and usage," Working Paper No. 12-06, Federal Reserve Bank of Richmond, 2012. [Online]. Available:

https://www.richmondfed.org/publications/research/working_papers/2012/wp_12-06

[22] M. A. de Oliveira, The Impacts of Pix on Merchant Discount Rates, Master's thesis, Politecnico di Torino, 2025.

[23] J.-C. Rochet and J. Tirole, "Two-sided markets: A progress report," The RAND Journal of Economics, vol. 37, no. 3, pp. 645–667, 2006. doi: 10.1111/j.1756-2171.2006.tb00036.x

[24] J.-C. Rochet and J. Tirole, "Must-take cards: Merchant discounts and avoided costs," Journal of the European Economic Association, vol. 9, no. 3, pp. 462–495, 2011. doi: 10.1111/j.1542-4774.2011.01020.x

[25] 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, J. Aurazo, J. Frost, and A. Kosse, Eds., BIS Papers No. 152, Bank for International Settlements, 2024, pp. 17–44. [Online]. Available: https://www.bis.org/publ/bppdf/bispap152.htm

[26] Z. Wang, "Market structure and payment card pricing: What drives the interchange?," Journal of Banking & Finance, vol. 34, no. 4, pp. 814–825, 2010. doi: 10.1016/j.jbankfin.2009.09.009

[27] J. Wright, "Pricing in debit and credit card schemes," Economics Letters, vol. 80, no. 3, pp. 305–309, 2003. doi: 10.1016/S0165-1765(03)00143-5

[28] European Central Bank, "TARGET Instant Payment Settlement (TIPS)," [Online]. Available: https://www.ecb.europa.eu/paym/target/tips/html/index.en.html. [Accessed: Jun. 18, 2026].

[29] European Parliament and Council of the European Union, Regulation (EU) 2015/751 of 29 April 2015 on interchange fees for card-based payment transactions, Official Journal of the European Union, L 123, pp. 1–15, 2015. [Online]. Available: https://eur-lex.europa.eu/eli/reg/2015/751/oj

[30] European Parliament and Council of the European Union, Regulation (EU) 2024/886 of 13 March 2024 amending Regulations (EU) No. 260/2012 and (EU) 2021/1230 and Directives 98/26/EC and (EU) 2015/2366 as regards instant credit transfers in euro, Official Journal of the European Union, L 2024/886, 2024. [Online]. Available: https://eur-lex.europa.eu/eli/reg/2024/886/oj

[31] M.-H. Felt et al., "Regressive effects of payment card pricing and merchant acceptance," 2023.

[32] European Central Bank, "Credit card interchange fees," ECB Working Paper Series No. 1138, European Central Bank, 2009.

[33] S. Chakravorti, "Externalities in payment card networks: Theory and evidence," Review of Network Economics, 2010.

[34] Bank for International Settlements, "Fast payments: design and adoption," 2024.

[35] Bank for International Settlements, "A revolution in digital payments: faster, user-friendlier and more inclusive," 2024.

[36] J. Pesme, "Fast payments offer potential for faster digital financial inclusion and faster growth," World Bank, 2023.

[37] World Bank, A Guide to Inclusive Instant Payment Systems, Washington, DC: World Bank.

[38] "The rise of instant payments: A cross-country comparison," [Online].

List of Figures

Figure 4.1 - Pix adoption after launch, 2020Q4-2025Q4 55
Figure 4.2 - Quarterly payment value by instrument 57
Figure 4.3 - Payment-value shares under the common denominator..... 59
Figure 4.4 - Average debit and credit merchant discount rates, 2005Q1-2025Q4 ... 61
Figure 4.5 - Credit-debit MDR spread 62
Figure 4.6 - Symmetric descriptive window around the Pix launch..... 63
Figure 4.7 - Distribution of MDR by calendar quarter 65
Figure 5.1 - Actual and fitted debit MDR in the baseline segmented ITS model 75
Figure 5.2 - Actual and fitted debit MDR in the baseline Pix-exposure model..... 76
Figure 5.3 - Actual and fitted credit MDR in the baseline segmented ITS model... 78
Figure 5.4 - Actual and fitted credit MDR in the baseline Pix-exposure model..... 79
Figure 5.5 - Actual and fitted debit MDR in the preferred dynamic ITS model 82
Figure 5.6 - Actual and fitted debit MDR in the dynamic Pix-exposure model..... 83
Figure 5.7 - Actual and fitted credit MDR in the preferred dynamic ITS model 85
Figure 5.8 - Actual and fitted credit MDR in the dynamic Pix-exposure model..... 86
Figure 5.9 - Actual and fitted quarterly changes in debit MDR..... 89
Figure 5.10 - Actual and fitted quarterly changes in credit MDR 90
Figure 5.11 - Actual and fitted MDR under dynamic nonlinear time trends 92
Figure 5.12 - Actual and fitted log MDR in the dynamic core models 94
Figure 5.13 - Actual and fitted MDR in the dynamic exposure-interaction models96
Figure 5.14 - Actual and fitted log MDR in the exposure-interaction models..... 97

List of Tables

Table 4.1 - Coverage of the quarterly master dataset 52
Table 4.2 - Descriptive statistics for principal variables 54
Table 4.3 - Selected Pix adoption milestones 56
Table 4.4 - Eight-quarter comparison around the Pix launch 64
Table 4.5 - Stationarity tests for the principal time-series variables 67
Table 5.1 - Payment-composition regression coefficients 73
Table 5.2 - Baseline and preferred dynamic MDR estimates 87
Table 5.3 - Diagnostic assessment of principal MDR specifications 102
Table 5.4 - Proposition and evidence hierarchy 104
Table 6.1 - Cost comparison between European and Brazilian instant payments systems 114

Acknowledgments

Writing this thesis marks the culmination of a profoundly transformative two-year journey. Taking the leap to move from Brazil to Italy has challenged me in ways I could never have anticipated and has massively expanded the boundaries of who I thought I was and who I aim to become.

To my family and friends back home, the physical distance often felt immense, but your constant support consistently fuelled me to strive for more. Thank you for keeping me grounded and for reminding me that no matter where my journey takes me, I will always have a home to miss.

To the friends who have become my chosen family in Italy: thank you for all the incredible moments and for making a foreign city feel a little bit like home, I am extremely fortunate to have lived these moments alongside you.

This experience has been a profound lesson: the importance of not just stepping into the unknown but learning how to cherish it. I end this journey not just with a degree, but with a wider view of the world and a greater appreciation for the life around me.

Thank you all for being part of this journey.

