Differentiated Impact of Spread Determinants by Personal Loan Category: Evidence from the Brazilian Banking Sector

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Abstract

The empirical literature on the determinants of banking spreads has considered banks as providers of one single product. According to this approach, the study of the effect of bank spreads determinants has assumed that this effect is uniform across the different types of loans offered by banks. The present study assesses the hypothesis that banking spreads attributes have a differentiated impact on spreads, according to the loan category. To this end, we adopt a dynamic model, estimated through System GMM on the basis of a dataset of interest spreads charged on three categories of personal loans in Brazil. Our results support the hypothesis of differentiated impacts according to loan category, and are corroborated by a robustness check, carried out through Difference GMM estimation of the adopted model. Overall, these findings also suggest that regulators should observe the composition of banks' loans portfolios when designing and implementing policies aiming at banking spread reduction.

Keywords: Banking spread; determinants; personal loans; financial sector.
JEL classification: G21; C23; E44.

1 Introduction

Financial intermediation efficiency can directly influence economic growth (Levine, 1997). Banking interest spreads—that is, the difference between lending interest rate and deposit interest rate—, in turn, are viewed by the World Bank (2005), as a quantitative measure of financial intermediation efficiency, especially in developing countries where commercial banks are the main source of financing for individuals and firms. This efficiency refers to the ability of the financial sector to provide high-quality products and services at the lowest possible cost. Accordingly, more efficient banking markets exhibit narrower spreads (World Bank, 2005).

Several studies have tried to explain the behavior of banking spreads so as to provide policymakers with insights about how to discipline interest margins and boost economic growth (e.g., Almeida & Divino, 2015; Hanzlík & Teplý, 2022; Lavezzolo, 2020). The theoretical milestone of this literature is the original model developed by Ho and Arnold s (1981), who adapted a bid-ask market price-setting model for bonds to explain banking spread behavior. Building on the literature about the determinants of the purchase price of securities, these Authors formulated a model in which the bank is considered a dealer in the credit market. [(1)] According to this model, both the supply of deposits and the demand for loans follow a random pattern, so that the time of entry and exit of funds cannot be predicted by the bank. Due to this uncertainty, the bank, which is viewed as a risk-averse entity, is encouraged to seek compensation for the risk of having a depositor claiming his funds before a borrower repays the loan. This compensation is the difference between the interest rate charged from loans and the interest rate paid on deposits. Under this model, four factors explain interest spreads: i. the degree of risk aversion; ii. the market structure in which the bank operates; iii. the average size of bank transactions; iv. the variance of interest rates. The Authors also showed that, even in a scenario of highly competitive banking markets, there must be an interest margin due to the uncertainty generated by asynchronous deposit supplies and loan demands. They called this margin "pure spread".

One limitation of Ho and Saunders (1981) model is that they assumed that the financial intermediaries offer just one kind of loan. The Authors draw attention to this limitation, stating that "extending the model from a structure with one kind of loan and deposit to loans and deposits with many maturities should lead to further interesting insights into margin determination, especially as 'portfolio' effects may become apparent" (p. 598). Allen (1988) extended the theoretical model incorporating the loan heterogeneity that can be observed in banks' portfolios. The Author demonstrated that pure interest spreads may be reduced when the portfolio effect is considered. The rationale for this behavior is that banks diversify their risk inventory exposure by controlling the relative rate spreads across product types.

Subsequently, several studies extended the dealership model adding new factors that influence the behavior of pure spread (e.g., Angbazo, 1997; Cruz-García & Fernández de Guevara, 2020; Maudos & Fernández de Guevara, 2004). In addition, numerous empirical studies have tested a multitude of bank-specific covariates, macroeconomic

(1) See also Ho and Stoll (1980), Ho and Stoll (1981), and Stoll (1978).

environment proxies, and variables related to the market structure of the banking sector, as potential determinants of bank interest margins. Some of these studies use multi-country panel data (e.g., Entrop et al., 2015; Jarmuzek & Lybek, 2020; Lavezzolo, 2020), others adopt a country specific approach (e.g., Almeida & Divino, 2015; Damane, 2020; Maudos & Solís, 2009). However, all of these studies have considered the banks as single product intermediaries, disregarding the portfolio effect demonstrated by Allen (1988). This approach assumes that the impact of the determinants of bank interest rate margins is uniform across the entire bank's loan portfolio. Allen's (1988) theoretical extension of the dealership model suggests that this may not be true. If there is indeed a portfolio effect in determining the banking spreads, then the impact of the determinants must vary among the spreads of the different loan types. The lack of informative data explains the apparent neglect of ignoring this possible variability: since banks do not usually disclose interest rates by type of loan (Brock & Suarez, 2000), estimating the impact of determinants of interest margins by bank product is impractical.

The present study addresses this gap, by investigating whether the impact of the determinants of banking spreads varies across different loan categories, as can be expected by considering the portfolio effect demonstrated by Allen (1988). This is done by estimating the impact of spreads' determinants, using a panel of interest rates charged by 13 Brazilian banks on three different personal loan categories: revolving credit, consumer loan, and payroll-linked loan. This dataset is rather informative as the Brazilian banking sector maintains one of the world's largest interest rate spreads (interest rate charged on loans minus interest rate paid on deposits). For example, in 2018, the country's average spread was 32.21%, while world average was 5.34%. [2]

The contribution of the present study to the extant literature is fourfold. Firstly, to the best of our knowledge, this is the first study to address and estimate the effect of the determinants of banking spreads considering different loan categories. In doing so, we provide an empirical assessment of the hypothesis of portfolio effect in banking spreads suggested by Allen (1988). No previous study has considered the potential heterogeneity that exists among loans' interest spreads when estimating the impact of their determinants. Spreads are usually computed based on accounting information, resulting in an average interest rate margin (or an average spread). The proxy commonly chosen is the

(2) International Monetary Fund, International Financial Statistics, and data files, available on http://data.worldbank.org/indicator/FR.INR.LNDP?view=map (Accessed November 2021).

net interest margin (NIM), defined as the ratio of the difference between total interest income and total interest expense, to the interest-bearing assets [(3)]. However, computing spreads using an average interest margin can be problematic for two main reasons. Spreads behave differently according to whether they are computed on the basis of accounting data or based on the difference between the lending interest rate and the deposit interest rate. For example, Afanasieff *et al*. (2002) argue that actual interest rates are more likely to be influenced by changes in the economic environment than by interest, income, and expenses. Almeida and Divino (2015), in turn, distinguish the spread computed by means of actual interest rates (termed "*ex-ante*" spread) from the spread computed by means of accounting data (termed "*ex-post*" spread). According to these Authors, the former is more volatile because it reflects the expectations of the banks with respect to the granting of credit before it is effectively granted. The *ex-post* spread tends to be more stable since it supposedly represents the effective result of the financial intermediation activity. In addition, estimation results may differ substantially if the interest spreads are computed based on accounting data or on disaggregated data (Brock & Franken, 2003).

Secondly, no previous study has estimated the impact of the determinants of the spreads of revolving credit, consumer loans or payroll-linked loans. This study provides evidence regarding these specific categories of loans. By considering different loan categories, we can analyze how the possibly unique characteristics of these types of loans impact their interest spread. For example, the average spread on revolving credit is much higher than the average spread on payroll-linked loans—possibly due to its different liquidity and credit risk profile. This allows the design of specific regulatory policies targeting the spread of each loan category.

Thirdly, this study offers evidence regarding the determinants of banking spreads using actual interest rates in the computation of the dependent variable, rather than proxies computed by averages taken from financial statements. Spreads computed using loan and deposit rates are arguably a better measure of banking efficiency than NIM (Agapova & McNulty, 2016). This is only possible with disaggregated data, obtained in the present case from the Central Bank of Brazil.

Finally, the study sheds additional light on the factors influencing the spreads in Brazil. Previous studies focusing on the Brazilian context have used a single proxy for banking spreads (e.g., Afanasieff et al., 2002; Almeida & Divino, 2015). By looking at

(3) Examples of studies using NIM as a proxy for the spread are provided by Cruz-García and Fernández de Guevara (2020), Hanzlík and Teplý (2022), and Kusi et al. (2020).

different types of loans, we provide additional information on the behavior of interest margins in the country.

The remainder of the paper is organized as follows. Section 2 presents the theoretical foundations that support our expectation of differentiated impacts of some attributes on the spread, for different loan categories. Section 3 details the variables, data, and econometric model used. Sections 4 and 5 present and comment on estimation results. Section 6 presents a robustness check. Section 7 concludes the paper, presents its limitations and suggests directions for further research.

2 Theoretical background

Ho and Saunders' (1981) dealership model considers that banks sell only one kind of loan, solving for bid-ask spreads when financial securities have correlated returns. In one extended version, Allen (1988) uses the same methodology (considering correlated returns among financial securities) with two kinds of loans (*m*-loans and *n*-loans) instead of only one. The complete Ho and Saunders solution of the pure spread for a single product intermediary comprises the sum of a measure of monopoly power and of the risk premium. Allen’s multiproduct solution differs from the single product case only in the last term of the equation, which evinces the cross-elasticity of demand across bank products (*m*- and *n*-type loans).

Allen argues that this interdependence of demands across banking services and products produces diversification benefits——if that were the case, there would be no margin for manipulating demand between loan categories according to the bank’s exposure to the risk provided by these same categories.

Allen's (1988) extension of Ho and Saunders' (1981) dealership model supports the main motivation of the present study, that is, the existence of a differentiated impact of banking spread determinants according to the loan category. However, one can question why a given attribute would have a stronger impact on the spread of a given loan category than on the spread of another. To address this issue, we need to clarify the reason behind the impact of certain attributes on the banking spread and how the loan categories analyzed in the study differ from each other in relation to these attributes.

The literature has considered mostly bank-specific characteristics, macroeconomic factors, and the structure of the financial industry as determinants of banking spread. For example, one of the main attributes analyzed is credit risk. According to Angbazo (1997), the bank's net interest margin should be higher because of higher required credit risk premium on bank loans. And we may ask how loan types differ from each other in terms of credit risk. Here, we analyze three loan categories: i. Revolving credit: credit available in deposit accounts allowing for the loan amount to be withdrawn or transferred, repaid, and redrawn again whenever and as often as the borrower wishes, without a fixed number of payments until the arrangement expires. In addition, this is a type of loan granted without the need for collateral. ii. Consumer loans: credit granted to individuals for personal, family or household expenses with monthly payments. This is a type of loan granted with few collateral requirements. iii. Payroll-linked loans for civil servants: loans whose instalments are directly debited in the civil servant's monthly paycheck. Looking closely at the characteristics of each type of loan, one can say that revolving loans have a higher credit risk than the other two categories. This is because, unlike the other two types of loan, there is no collateral required in revolving loans. In addition, no installment amount is set, and borrowers can pay at the time that suits them best, without commitment to a specific repayment date (provided they pay interest). Conversely, the other two categories require some sort of collateral, and both have specific installments and payment dates. Consumer loans, in turn, seem to have higher credit risk than payroll-linked loans. This is because in consumer loans the guarantee required is usually a guarantor's commitment to repay the loan if the borrower defaults. In payroll-linked loans, the installment is debited directly from the borrower's monthly salary. Clearly, the guarantee is weaker for consumer loans, since the consumer loan guarantor can strategically default, whereas in payroll-linked loans the debit is not paid only if the borrower loses his/her job. Therefore, credit risk should impact the revolving credit spread more strongly than consumer loans and payroll-linked loans spreads, and it should influence less payroll-linked loans spreads than consumer loans spreads.

One other example is provided by implicit interest payments. Saunders and Schumacher (2000) argue that banks are encouraged to increase their interest margins to finance implicit interest on deposits. The three loan categories analyzed in this paper differ in relation to this attribute. The Central Bank of Brazil prevents the country's financial institutions from charging fees on revolving credit accounts, but not on consumer loans neither on payroll-linked loans. The fee waiver is a kind of implicit interest paid to borrowers of revolving credit that are not paid to consumer or payroll-linked loans clients. Thus, revolving credit spreads should be expected to be more strongly affected by implicit interest payments than the other two loan categories.

A third example is economic growth. Claessens et al. (2001) explain the positive relationship between economic growth and banking spreads arguing that improved welfare indicates increased ability to service debt obligations. In this sense, banks take advantage of the economic growth scenario to increase their interest spreads. Again, the three loan categories analyzed in this study differ in terms of the influence of economic growth due to their characteristic credit risk profile. As revolving credit is the category with the highest credit risk, it should also be the one that best benefits from an increased ability to service debt obligations. Thus, it should offer more room for spreads to widen in a scenario of economic growth than the other two categories.

Following this logic, the relationship between the characteristics of each type of loan and the attributes that influence banking spreads can cause these attributes to have a differential impact on the spread of different lines of credit. Given that each category has regulatory characteristics specific to each country or financial market, the focus of this study is not on developing hypotheses for each of the attributes that influence banking spreads. Rather, we are concerned with testing the hypothesis under which the determinants of banking spreads can have a differentiated impact depending on the loan category analyzed.

3 Data and Econometric Model

3.1 Data and Variables

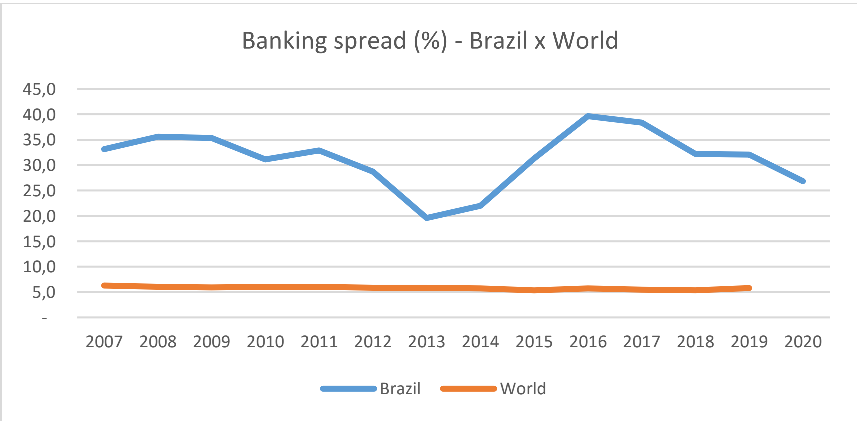
To test the hypothesis of a differentiated impact of spread determinants across different loan categories, this study uses data from the Central Bank of Brazil. Brazil is the largest economy in Latin America and the 12th largest economy in the world, with a nominal GDP of $ 1.44 trillion. (4) The Brazilian banking industry is the primary distributor of financial products and services in the country. It is also heavily concentrated, with only five banks accounting for 70% of the outstanding commercial loans by the end of June 2021.

High interest rates charged on loans contribute to keep the country's average bank spread among the highest in the world, despite the sharp decline observed after the economic stabilization program called Real Plan, launched in June 1994. This program ended

[4] World Bank database, available on https://databank.worldbank.org/data/download/GDP.pdf (Accessed November 2021).

a long period of hyperinflation, and the average banking spread of the country dropped from 53.8%, in 1997, to 33.1% in 2007. In 2012, the Brazilian government began using state-owned banks to force the country's financial system to further reduce spreads charged on bank loans. As a result, the average banking spread reached one of its lowest levels ever, dropping from 32.9%, in 2011, to 19.6%, in 2013. However, inflation, which had been under control, returned to high levels, forcing the Central Bank to raise the basic interest rate again. Between mid-2014 and 2016, the country plunged into the most intense economic recession in its history, and Brazil's economy shrank 7% in the 2015-16 biennium. In 2016, the country's average banking spread had again doubled to 39.6% according to the World Bank. The subsequent drop in inflation allowed for a new cycle of reduction in the basic interest rate, which reached is lowest level in August 2020. In 2020, the average banking spread of the country was 26.8%, still one of the highest in the world. Figure 1 shows these movements in the country's banking spread. The high spreads have been the subject of studies and one target of government regulators given their negative effects on Brazil's economic growth.

Figure 1 – Behavior of the Brazilian banking spread



The size of the Brazilian economy and its long history of high interest rate spreads charged in its banking sector make the country an appropriate context for studying the determinants of spreads by loan category. The Brazilian economy is highly representative in the Latin American economy, which means that Brazilian regulatory policies have an impact in other countries in the region. The high level of interest rates charged in the country, in turn, allows capturing more accurately variations in the impact of factors that influence the behavior of the banking spread.

The dataset used in the present study is composed of interest rates charged by 13 Brazilian banks in three categories of loans targeted at individuals, from January 2012 to June 2021 on a semiannual basis (nineteen semesters). (5) The sample can be considered representative of the Brazilian financial sector, as these 13 banks account for 70% of the total assets and 74% of the outstanding credit operations held by commercial institutions in the country in June 2021. (6) Seven of these 13 banks are state-owned and one is a foreign bank with operations in Brazil.

As mentioned in Section 2, the three loan categories analyzed in this study are revolving credit, consumer loans, and payroll-linked loans for civil servants. The semiannual basis is obtained by averages computed from the released weekly data. There is no public data on loan proceeds in each category, so the average computed is a simple average. The resulting sample comprises 57 observations (19 semesters for each of the three loan categories) for each of the 13 banks, with an overall total of 741 observations.

The dependent variable in this study is the difference between the average interest rate charged on each loan category and a proxy for the deposit interest rate – the Financial Basic Interest Rate (TBF). We use this proxy because the deposit interest rates are not available on a bank-specific basis. The TBF is deemed an adequate proxy for deposit interest rates because it is based on the average rate paid on certificates of deposits of the largest banks in the country. (7)

The set of covariates includes the main vectors used in the empirical literature, that is: i. bank-specific characteristics; ii. macroeconomic factors; iii. the structure of the financial industry. The first group of covariates includes credit risk, liquidity risk, risk aversion, operating costs, implicit interest payments, and opportunity cost of non-interest-bearing reserves. Credit risk (*CrtRsk*) is measured as the ratio of provision for loan

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(5) The banks included in our sample are: Banco Bradesco, Banco Santanter do Brasil, Banco do Estado do Rio Grande do Sul, Caixa Econômica Federal, Banco do Brasil, Itaú Unibanco, Banco Daycoval, Banco do Estado do Espírito Santo, Banco Mercantil do Brasil, Banco do Estado de Sergipe, Banco do Estado do Pará, Banco de Brasília, and Banco Safra.

(6) Data available at https://www.bcb.gov.br/estabilidadefinanceira/balancetesbalancospatrimoniais (Accessed November 2021).

(7) Deposit rates offered by banks exhibit low variability. Banks do not provide interest rates paid on deposits on their websites, but on a survey carried out on 03/09/2021 at the websites of two of the country's main financial distributors (www.xpi.com.br and www.btgpactual.com.br), the average deposit rate offered by 25 banks was 5.53% per year, with a standard deviation of 0.48%. This variation was partly due to the difference in maturities. If only six months maturities are considered, the average deposit rate was 6.09%, with an even smaller standard deviation of 0.28%.

operations to gross credit operations. Liquidity risk (*LqtRsk*) is computed as the ratio of liquid to total assets. Liquid assets include cash and deposit balances in other banks. Risk aversion (*RskAvs*) is proxied by the ratio of equity to total assets. Operating costs (*OprCst*) are measured as administrative expenses to total assets. Implicit interest payments (*ImpInt*) are computed as the difference between non-interest expense and non-interest income to earning assets. Earning assets refer to assets that generate income like interest or dividends. [8] The opportunity cost of holding reserves (*OppRsv*) is measured as the ratio of cash balances to total assets.

The macroeconomic covariates include the inflation rate, the basic interest rate, interest risk, and GDP growth. Inflation rate (*Infl*) is the half-yearly inflation rate, as measured by the Consumer Price Index (IPCA). The basic interest rate (*Selic*) is the average interbank goal rate released by the Central Bank in the last semester. Interest risk (*IntRsk*) is captured by the moving standard-deviation of the basic interest rate, considering the last four semesters. GDP growth (*GDPg*) is the half-yearly GDP growth rate.

The market structure variable is represented by market power and state ownership. Market share (*MktSh*) captures the market power of the bank and is measured as the ratio of the bank's credit operations to the total credit operations of the Brazilian banking sector. State ownership is represented by a dummy variable (*SttOwn*) that takes the value 1 if the bank is state-owned and 0 otherwise. Table 1 presents the study's *a priori* expectations regarding the sign of the explanatory variables, refers the main studies supporting these *a priori* expectations and presents a summary of how the variables were obtained.

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[8] Loans and securities are the main examples of bank earning assets, among others, like leased or rented buildings that earn income.

Table 1

A priori expectations and operationalization of the variables

Variable	Computation	Expected sign	Rationale	References
CrtRsk	$\frac{Provision\ for\ loan\ operations}{Revenue\ from\ credit\ operations}$	Positive	Banks with riskier loans should charge higher spreads to make up for default losses.	Agoraki and Kouretas (2019); Hanzlík and Teplý (2022); Kusi et al. (2020)
LqtRsk	$\frac{Liquid\ assets}{Total\ assets}$	Positive/ Negative	Positive: high liquidity ratios come at a cost since banks must forgo higher yielding assets, leading to higher interest spreads. Negative: the higher the proportion of liquid funds, the lower the liquidity risk, leading to lower liquidity premium in the interest spread.	Agoraki and Kouretas (2019); Angbazo (1997); Demirguç-Kunt et al. (2004); Nguyen (2012); Peria and Mody (2004)
RskAvs	$\frac{Equity}{Total\ assets}$	Positive	The higher the ratio between equity and total assets, the higher the risk aversion of the managerial team, leading to higher risk premium in the spread.	Brock and Suarez (2000); Hanzlík and Teplý (2022); Saunders and Schumacher (2000)
OprCst	$\frac{Administrative\ expenses}{Total\ assets}$	Positive	Banks with higher operating costs should charge higher spreads to make up for higher administrative expenses.	Cruz-García and Fernández de Guevara (2020); Peria and Mody (2004); Carbó-Valverde, and Rodríguez-Fernández (2007)
ImpInt	$\frac{Noninterest\ expenses - noninterest\ revenues}{Earning\ assets}$	Positive	Banks should charge higher spreads to compensate higher implicit interest payments.	Agoraki and Kouretas (2019); Entrop et al. (2015); Lin et al. (2012)
OppRsv	$\frac{Cash\ balances}{Total\ assets}$	Positive	The higher the proportion of funds invested in no-interest bearing reserves, the higher the compensation requested by the bank and the higher the interest spread.	Hawtrey and Liang (2008); Lavezzolo (2020); Maudos and Fernández de Guevara (2004)
Infl	*Half-yearly inflation rate as measured by the consumer price index (IPCA)*	Positive	Inflation rate is considered a component of the cost of doing business. Higher levels of inflation should lead to higher interest spreads.	Entrop et al. (2015); Lavezzolo (2020); López-Espinosa et al. (2011)
Selic	*Selic interest rate*	Positive	The basic interest rate is the main cost of money. A higher cost of money should encourage banks to charge higher interest spreads.	Gelos (2009); Hanzlík and Teplý (2022); Lepetit et al. (2008)
IntRsk	*Moving standard-deviation of the Selic*	Positive	Greater volatility of the basic market interest rate should encourage banks to	Entrop et al. (2015); López-Espinosa et al.

Variable	Computation	Expected sign	Rationale	References
	rate, considering the last four semesters		include a higher market risk premium into the interest spreads.	(2011); Maudos and Solís (2009)
GDPg	*Half-yearly real GDP*	Positive/ Negative	Positive: an economic growth scenario signals a greater ability to pay interest, encouraging banks to charge higher spreads. Negative: an economic growth scenario also signals a lower risk of default by borrowers, leading banks to charge lower spreads.	Chortareas et al. (2012); Entrop et al. (2015); Hanzlík and Teplý (2022); Kasman et al. (2010); Kusi et al. (2020)
MktSh	$\frac{Credit\ operations}{Total\ credit\ operations\ of\ the\ Brazilian\ banking\ system}$	Positive	A more concentrated banking system, with less competition, makes it easier for banks to charge higher interest spreads.	Almeida and Divino (2015); Maudos and Fernández de Guevara (2004); Peria and Mody (2004)
SttOwn	*Dummy variable taking the value 1 if a state-owned bank and 0 otherwise*	Negative	State-owned banks are more subject to political pressures to reduce interest spreads.	Demirguç-Kunt et al. (2004)

The data used to compute bank-specific variables were extracted from half-yearly financial statements reported to the Central Bank of Brazil by the financial institutions through Document 4010. (9) Information regarding each financial institution was used, rather than the financial conglomerate, because the present focus is solely on credit operations. Since financial conglomerates may include data related to brokers, investment banks, foreign branches, etc., banks with an active loan portfolio seem more adequate for this empirical analysis. The data used in the computation of macroeconomic variables were collected from the Brazilian Institute of Geography and Statistics (IBGE) and from the Central Bank of Brazil's website. (10)

Table 2 displays descriptive statistics for all variables. The heterogeneity among loans' spreads is rather high: spreads vary from a minimum of 8.5%, for payroll-linked loans for civil servants, to a maximum of 856%, for consumer loans. Revolving credit exhibits a notoriously high average spread of 202.8%. By comparison, the average spread of consumer loans is considerably smaller, but this category still has a high average of 89.5%. Spreads are smallest for payroll-linked loans: 16.2%, on average. A possible

(9) Document 4010 is a form containing information on the financial institution's balance sheet and income statement. Data available at http://www4.bcb.gov.br/fis/cosif/balancetes.asp (Accessed November 2021).
(10) Data available at https://www.bcb.gov.br/?SERIESTEMP (Accessed November 2021).

explanation for the disparity of spreads for the three categories is the risk level of each category. Clearly, the default risk for revolving credit loans and consumer loans is greater than the default risk for payroll-linked loans given that the payroll-linked loans installments are directly debited from the civil servants' monthly salary. Revolving credit also presents greater liquidity risk when compared to the other two categories, as there is no predefined date for withdrawal or repayment in this loan category: Borrowers are free to take the money and return it whenever they want, as long as they pay interest. There is also a high degree of variation among the spreads of the same loan category across the 13 banks in the sample. This is due to the different business models of the banks. There are banks with national activities (e.g., Bradesco, Caixa Econômica Federal, Banco do Brasil, Itaú Unibanco) and regional banks (e.g., Banco do Estado do Espírito Santo, Banco de Brasília). There are also commercial banks (e.g., Banco Safra, Banco Mercantil do Brasil) and banks with an emphasis on development activities (e.g., Banco do Estado do Pará, Banco do Estado de Sergipe).

Two bank-specific variables exhibit a high degree of variation, reflecting the heterogeneity of the 13 banks included in the sample. For example, *MtkSh* has a maximum value of 26.4%, 377 times higher than the minimum of 0.07%, which shows the disparity in the market power of the banks in the sample. The difference between maximum and minimum values in *OppRsv* also shows that the efficiency in the management of banking reserves varied considerably within the panel. The remaining bank-specific variables *LqtRsk*, *ImpInt*, *OprCst*, *RskAvs*, and *CrtRsk* also exhibit substantial—though smaller—variation. As for macroeconomic attributes, the corresponding variables suggest that the Brazilian economy experienced a roller coaster-type movement during the time span considered, with inflation rate varying from 0.10% in the most stable semester to 6.17% in the most troubled one; the interbank base interest rate ranged from a minimum of 1.95% to a maximum of 14.15%; in this period the economy experienced both a tumble of -2.91% and an increase of 3.22% .

Table 2
Descriptive Statistics

Variable	Mean	Median	Std. Dev.	Min.	Max.
Spread (%)					
Revolving credit	202.75	169.15	105.82	53.36	533.73
Consumer loans	89.54	58.18	117.16	18.72	856.00
Payroll-linked loans (civil servants)	16.21	15.70	3.65	8.51	29.25
CrtRsk	6.47	6.03	2.37	2.18	13.06
LqtRsk	20.61	19.41	9.36	1.33	52.20
RskAvs	7.85	7.75	2.79	2.02	17.23
OprCst	2.08	1.43	1.28	0.58	5.50
ImpInt	0.97	0.33	1.94	-3.20	8.05
OppRsv	1.44	1.09	1.54	0.12	13.33
Infl	2.83	2.60	1.44	0.10	6.17
Selic	8.59	8.35	3.79	1.95	14.15
IntRsk	1.61	1.54	0.71	0.48	3.36
GDPg	0.11	0.67	1.57	-2.91	3.22
MktSh	5.49	1.05	7.74	0.07	26.36
SttOwn	0.54	1.00	0.50	.00	1.00

All variables are expressed as a percentage, except SttOwn (dummy variable). Check Table 1 for description of variables.

3.2 Econometric Model

In this study, we apply the standard methodology of dynamic panel analysis. We adopt a dynamic specification, in line with what is usually preferred in the spread determinants' literature (Cruz-García & Fernández de Guevara, 2020; Kusi et al., 2020), due to the persistence of bank interest margins over time (Berger et al., 2000).

For each bank and loan type (index i) and semester (index t), the general form of our dynamic econometric model can be expressed as

$$Spread_{it} = \alpha_i + \xi_1 Spread_{i,t-1} + \sum_{j=1}^{12} \beta_j x_{it}^j + \xi_2 (Spread_{i,t-1} \times Cons_i) + \sum_{j=1}^{12} \gamma_j (x_{it}^j \times Cons_i) + \xi_3 (Spread_{i,t-1} \times Payroll_i) + \sum_{j=1}^{12} \delta_j (x_{it}^j \times Payroll_i) + u_{it}. \quad (1)$$

where ξ_1, ξ_2, ξ_3, β_j, γ_j and δ_j $(j = 1, \dots, 12)$ denote unknown parameters to be estimated. In this equation, the dependent variable, $Spread$, represents banking spread and x_{it}^1, …,

x_{it}^{12} denote the following covariates (covariates' acronyms as defined in Table 1): x_{it}^{1}—$CrtRsk_{it}$; x_{it}^{2}—$LqtRsk_{it}$; x_{it}^{3}—$RskAvs_{it}$; x_{it}^{4}—$OprCst_{it}$; x_{it}^{5}—$ImpInt_{it}$; x_{it}^{6}—$OppRsv_{it}$; $x_{it}^{7} \equiv x_{t}^{7}$—$Infl_{t}$; $x_{it}^{8} \equiv x_{t}^{8}$—$Selic_{t}$; $x_{it}^{9} \equiv x_{t}^{9}$—$IntRsk_{t}$; $x_{it}^{10} \equiv x_{t}^{10}$—$GDPg_{t}$; x_{it}^{11}—$MktSh_{it}$; $x_{it}^{12} \equiv x_{i}^{12}$—$SttOwn_{i}$. As mentioned, the indices (i, t) refer, respectively, to each pair bank/loan-type (index i), and semester (index t). [(11)] The unobservable variables, α_i and u_{it}, denote, respectively, an individual effect (time-invariant, $\alpha_{it} = \alpha_i$, $\forall t$), possibly correlated with covariates, and the random error, uncorrelated with both α_i and the model's explanatory variables.

The base loan category is revolving credit, for which the dummy variables $Cons$ and $Payroll$ are both null. $Cons$ is equal to one if the loan is a consumer loan ($Cons = 0$, otherwise). The dummy variable $Payroll$ equals one if the loan is a payroll-linked loan for civil servants ($Payroll = 0$, otherwise). The use of these two dummies allows for three possibly distinct sub-regressions, underlying equation (1). Under this approach we can easily identify—and test the significance of—the possibly differentiated impacts of the covariates on banking spread, across loan-type. For each loan category, the resulting regression equation is, respectively,

i. Regression for the loan base category—revolving credit ($Cons = Payroll = 0$),

$$Spread_{it} = \alpha_i + \xi_1 Spread_{i,t-1} + \beta_1 CrtRsk_{it} + \cdots + \beta_{12} SttOwn_i + u_{it};$$

ii. Regression for consumer loans ($Cons = 1$, $Payroll = 0$),

$$Spread_{it} = \alpha_i + (\xi_1 + \xi_2) Spread_{i,t-1} + (\beta_1 + \gamma_1) CrtRsk_{it} + \cdots + (\beta_{12} + \gamma_{12}) SttOwn_i + u_{it};$$

iii. Regression for payroll-linked loans ($Cons = 0$, $Payroll = 1$),

$$Spread_{it} = \alpha_i + (\xi_1 + \xi_3) Spread_{i,t-1} + (\beta_1 + \delta_1) CrtRsk_{it} + \cdots + (\beta_{12} + \delta_{12}) SttOwn_i + u_{it}.$$

Due to the presence of the time-invariant effect, α_i, the model error term, $\alpha_i + u_{it}$, is obviously correlated with the lagged dependent variable across different periods. For

[11] The consideration of the pair bank/loan type as the basic cross-sectional unit (rather than solely the bank) enables the specification of a univariate regression model easily addressed with current econometrics packages (such as Stata). Otherwise, one would have to specify a multivariate regression model for panel data, with three dependent variables (three interests' spreads) for each cross-sectional unit (bank) in each period.

this reason, we used system GMM, developed by Arellano and Bover (1995) and Blundell and Bond (1998). System GMM is designed for dynamic models with independent variables that are correlated with past and possibly current realizations of the error (i.e., not strictly exogenous) and fixed individual effects. Some care must be taken, however, to ensure the consistency of the estimates, given that system GMM relies on the assumption of mean stationarity of the panel. We carry out the Hansen overidentification test, to verify whether the instruments, as a group, are exogenous. One must also avoid the usage of many instruments because this can overfit endogenous variables and weaken the Hansen test. In addition, the model will be adjusted in case of multicollinearity issues in the explanatory variables.

In order to assess the presence of autocorrelation, the test proposed by Arellano and Bond (1991), applied to the residuals in differences, is performed. Usually, the null hypothesis of no first order autocorrelation, AR(1), is rejected because $\Delta u_{i,t} = u_{i,t} - u_{i,t-1}$ is mathematically related to $\Delta u_{i,t-1} = u_{i,t-1} - u_{i,t-2}$, given that both share the common term $u_{i,t-1}$. Therefore, to check for first-order serial correlation in levels, the second order correlation in differences is considered (Roodman, 2009). We use the two-step GMM estimation technique, which controls and corrects for both heteroscedasticity and autocorrelation (Windmeijer, 2005). The estimation also uses the Windmeijer's (2005) correction, without which the standard errors computed in two-step results would be severely downward biased.

4 Empirical Results

In order to test for stationarity, we perform the unit root tests proposed by Levin, Lin, and Chu (2002) and by Im, Pesaran, and Shin (2003)—shortly labelled as LLC and IPS, respectively. Table 3 presents the results of data unit root tests. The deterministic terms listed in the table are used in the test equations. The cross-sectional averages are subtracted from the series to reduce the impact of cross-sectional dependence (Levin et al., 2002) in three out of four tests. To address the possible problem of serial correlation in the model, the test equations are augmented with 2 lags, in accordance with the half-yearly frequency of the variables.

Table 3

Panel data unit root tests

Variable	LLC No const	LLC Const	IPS Const	IPS Nodemean
CrtRsk	-2.83***	-.83	-1.06	-2.12**
LqtRsk	-4.10***	1.59	-1.59*	-1.69**
RskAvs	-5.71***	-3.90***	.64	1.24
OprCst	-1.02	-1.39*	.65	2.62
ImpInt	-3.50***	.30	-1.43*	-1.32*
OppRsv	1.30	4.82	3.90	-.14
MktSh	1.01	-2.38***	-1.80**	4.78

*** The null hypothesis of unit root is rejected at the 1% significance level.
** The null hypothesis of unit root is rejected at the 5% significance level.
* The null hypothesis of unit root is rejected at the 10% significance level.
Check Table 1 for description of variables.

OppRsv raises some concern since the null hypothesis of the presence of a unit root is not rejected at the 10% significance level in any of the four estimated models. *OprCst* is also worrisome given the rejection in only one model. The stationarity of the time series is evaluated by the test proposed by Elliott et al. (1996). The results are reported in Table 4, including the deterministic terms used in the test equation.

Table 4

Time series unit root tests

Variable	Lags	Trend		No trend	
		t-Stat	5% C.V.	t-Stat	5% C.V.
Infl	1	-2.06	-3.50	-1.93	-2.57
Selic	2	-1.64	-3.35	-0.98	-2.51
IntRsk	2	-2.17	-3.50	-2.12	-2.51
GDPg	2	-2.08	-3.35	-1.95	-2.51

Null hypothesis: presence of unit root. Check Table 1 for description of variables.

One can see that the null hypothesis of unit root is not rejected in any of the estimated models. Given that the Brazilian time series usually present structural breaks that can affect the performance of unit root tests, the test by Zivot and Andrews (1992) is used, allowing for a structural break in intercept and/or trend. The fraction of data range to skip at either end when examining possible break points can be set between 0% and 25%. The Akaike information criteria minimizing value is used for deciding the number of additional lags. Table 5 presents mixed results. After accounting for the presence of a structural break in the intercept, the null hypothesis of unit root is rejected in all models. But when accounting for the presence of structural break in both intercept and trend, the null hypothesis cannot be rejected in any model.

Table 5

Time series unit root tests – structural break

Variable	Lag	Fraction of data range: 5%				Fraction of data range: 20%			
		Intercept		Intercept/Trend		Intercept		Intercept/Trend	
		T-stat	5% C.V.	T-stat	5% C.V.	T-stat	5% C.V.	T-stat	5% C.V.
Infl	0	-5.21	-4.80	-4.93	-5.08	-5.21	-4.80	-4.93	-5.08
Selic	1	-4.95	-4.80	-4.80	-5.08	-4.95	-4.80	-4.80	-5.08
IntRsk	1	-6.65	-4.80	-8.02	-5.08	-6.65	-4.80	-8.02	-5.08
GDPg	1	-3.46	-4.80	-3.87	-5.08	-3.46	-4.80	-3.87	-5.08

Null hypothesis: presence of unit root. Check table 1 for description of variables.

In addition to the stationarity of the panel, one other concern relates to the possible presence of multicollinearity. The Pearson's correlation matrix was used to exclude variables with correlational value exceeding 0.7 threshold, which are deemed multicollinear following Kennedy (2008). The interactions between the dummy variables *Cons* and *Payroll* and the variables *CrtRsk*, *LqtRsk*, *RskAvs*, *Infl*, and *IntRsk* were excluded from the model in this process, as well as the interaction between the dummy variable Payroll and $Spread_{t-1}$. (12) The practical motivation to include the interactive variables in the correlation matrix is to limit the number of instruments used. Given the large number of regressors (38), the number of instruments used is relatively large compared to the number of individual units (39) in the panel, which can bias the results. (13)

This means that we did not test the hypothesis of differential impact of these determinants on consumer loans and payroll-linked loans spreads comparatively to revolving credit spreads. The variable *OprCst* and its interactions with the dummies *Cons* and *Payroll* were also excluded given the correlational value above 0.7 threshold. The final estimated model was then as follows:

[12] The correlation matrix is shown in the appendix.
[13] Conversely, the bias is also present when instruments are few.

$$
\begin{gathered}
Spread_{it} = \alpha_i + \qquad (2) \\
\xi_1 Spread_{i,t-1} + \xi_2 (Spread_{i,t-1} \times Cons_i) + \\
\beta_1 CrtRsk_{it} + \beta_2 LqtRsk_{it} + \beta_3 RskAvs_{it} + \\
\beta_5 ImpInt_{it} + \gamma_5 (ImpInt_{it} \times Cons_i) + \delta_5 (ImpInt_{it} \times Payroll_i) + \\
\beta_6 OppRsv_{it} + \gamma_6 (OppRsv_{it} \times Cons_i) + \delta_6 (OppRsv_{it} \times Payroll_i) + \\
\beta_7 Infl_t + \\
\beta_8 Selic_t + \gamma_8 (Selic_t \times Cons_i) + \delta_8 (Selic_t \times Payroll_i) + \\
\beta_9 IntRsk_t + \\
\beta_{10} GDPg_t + \gamma_{10} (GDPg_t \times Cons_i) + \delta_{10} (GDPg_t \times Payroll_i) + \\
\beta_{11} MktSh_{it} + \gamma_{11} (MktSh_{it} \times Cons_i) + \delta_{11} (MktSh_{it} \times Payroll_i) + \\
\beta_{12} SttOwn_i + \gamma_{12} (SttOwn_i \times Cons_i) + \delta_{12} (SttOwn_i \times Payroll_i) + \\
+u_{it}.
\end{gathered}
$$

Estimation results are displayed in Table 6. The reader can notice that some determinants are not followed by their respective interactions. This happens because, as aforementioned, we excluded all the variables and interactions with a correlational value above 0.7.

Table 6

Determinants of Interest Rate Spreads – Estimation Results (System GMM)

Variable	Coefficient (p-value)
$Spread_{i,t-1}$	0.85 (0.000)
$Spread_{i,t-1} \times Cons_i$	0.06 (0.384)
$CrtRsk_{it}$	1.26 (0.497)
$LqtRsk_{it}$	0.38 (0.133)
$RskAvs_{it}$	3.23 (0.018)
$ImpInt_{it}$	8.52 (0.052)
$ImpInt_{it} \times Cons_i$	-10.82 (0.230)
$ImpInt_{it} \times Payroll_i$	-5.35 (0.258)
$OppRsv_{it}$	-8.79 (0.002)
$OppRsv_{it} \times Cons_i$	18.58 (0.000)
$OppRsv_{it} \times Payroll_i$	0.50 (0.919)
$MktSh_{it}$	2.28 (0.088)
$MktSh_{it} \times Cons_i$	-1.51 (0.284)
$MktSh_{it} \times Payroll_i$	-2.33 (0.219)
$Infl_t$	3.22 (0.003)
$Selic_t$	4.80 (0.000)
$Selic_t \times Cons_i$	-3.79 (0.005)
$Selic_t \times Payroll_i$	-3.88 (0.000)
$IntRsk_t$	-1.10 (0.469)
$GDPg_t$	8.11 (0.000)
$GDPg_t \times Cons_i$	-5.54 (0.001)
$GDPg_t \times Payroll_i$	-8.11 (0.000)
$SttOwn_i$	-26.97 (0.053)
$SttOwn_i \times Cons_i$	2.86 (0.927)
$SttOwn_i \times Payroll_i$	38.26 (0.011)
$Constant$	-54.01 (0.039)

The two-step System GMM estimators with robust errors is used; *p*-values in parenthesis. Number of observations: 702. Wald chi^2 *p*-value ≈ 0.000. Arellano-Bond AR (1) *p*-value = .093; Arellano-Bond AR (2) *p*-value = .271. Hansen overidentification test: *p*-value = .975. Difference-in-Hansen test *p*-value

= 1.000. GMM set of instruments: 2rd lag of spread. Total number of instruments used: 56. Check table 1 for description of variables.

Overall, the model is well specified, according to the diagnostic tests on the estimated residuals for dynamic panel data. According to the Arellano-Bond AR (2) test, there is no evidence of second order autocorrelation in the residuals at the standard 5% significance level. The Hansen test of over-identifying restrictions, which tests the overall validity of the instruments, indicates that the set of instruments are orthogonal to the estimated residuals.

5 Discussion

The estimated coefficient of the lagged dependent variable suggests that 85% of the current spread of revolving credit loans is explained by the last period spread of this loan category. This inertial effect was also found by previous studies that use net interest margin (NIM) as a proxy of banking spread (e.g., Cruz-García & Fernández de Guevara, 2020; Hanzlík & Teplý, 2022; Kusi et al., 2020). Four bank-specific variables are statistically relevant. The estimated coefficient of *RskAvs* is positive, indicating that the larger the bank's risk aversion, the larger the spread of revolving credit. This result is explained by the demand for financial compensation for taking more risks. The coefficient of *ImpInt* is also positive and statistically significant, but not the coefficients of its interactive terms, suggesting that implicit interest payments costs are passed on to borrowers of revolving credit, but not on to borrowers of consumer or payroll-linked loans. This can be explained by the restriction established by the Central Bank of Brazil on charging fees for revolving credit – so banks have a lower revenue in this category and charge a higher spread to compensate for the ban on charging fees for revolving credit. The positive coefficients of *RskAvs* and *ImpInt* are present in studies using NIM, like Hanzlík and Teplý (2022) and Agoraki and Kouretas (2019).

OppRsv has a negative estimated parameter. This may seem counterintuitive *a priori*, considering that for revolving credit banks should maintain larger cash balances, given the uncertainty regarding deposits and withdrawals in this category. However, this negative relationship is highly compensated by the positive coefficient of *OppRsv x Cons*. To interpret the impact of the opportunity cost of holding reserves on the spread of consumer loans, one must add the coefficients of the interactions to the coefficient of the reference loan category. The coefficient of *OppRsv x Cons* is large enough to make the relationship between the opportunity cost of holding reserves and the spread of consumer loans positive. This suggests some degree of subsidization between those two categories. Conversely, there is no statistically significant relationship between that cost and the spread of payroll-linked loans. One explanation for the lack of statistical significance in this variable is that payroll-linked loans have greater predictability in both disbursement and reimbursement of funds (especially in the latter, considering that payment is made directly on the customer's paycheck). *MktSh* has the expected positive coefficient, but its interaction terms are not statistically relevant. This is indicative of less competition in revolving credit when compared to the other two loan categories. Thus, banks can impose their market power in this category.

The macroeconomic variables *Infl*, *Selic*, and *GDPg* have statistically significant coefficients, all with the expected signs. The positive relationship between *Infl* and spread indicates that inflationary costs are also passed on to borrowers of revolving credit loans. This result is in line with previous studies using NIM, like Hanzlík and Teplý (2022) and Lavezzolo (2020). Inflation is a cost for the bank, so the bank can be expected to pass this cost on to its customers. The same reasoning applies to the interbank rate, Selic. *Selic* and its interactions were also statistically significant. The expected positive sign of the coefficient of *Selic* suggests that the higher the basic interbank interest rate, the higher the spread of revolving credit, in line with previous findings using NIM (e.g., Gelos, 2009; Hanzlík & Teplý, 2022; Lepetit et al., 2008).

By adding the coefficients of *Selic* and of *Selic x Cons* one still obtains a positive estimate, suggesting a positive relationship between the basic interbank rate and the spread of consumer loans. However, this impact is lower than the impact observed on the spread of revolving credit. The result is roughly the same when adding the negative coefficient of *Selic x Payroll* to the positive coefficient of *Selic*. This result indicates that there is no substantial difference in the impact of the interbank rate on the spreads of consumer or payroll-linked loans. The difference in the impact on the spread of these two categories and on the spread of revolving credit is likely explained by the large difference in the average interest rates charged between those loan categories.

The positive coefficient of *GDPg* suggests that periods of economic growth stimulate banks to charge higher spreads in revolving credit loans, probably due to a perception by banks that revolving credit customers have the capacity to pay higher spreads in periods of economic boom. A positive relationship between economic growth and banking spreads had already been found by previous studies using NIM, like, Kusi et al. (2020) and Almeida and Divino (2015). The relationship is also positive between economic growth and the spreads of consumer loans, although to a lesser extent. The negative coefficient of *GDPg x Payroll*, in turn, when added to the coefficient of GDPg, results in a null impact of economic growth on the spread of payroll-linked loans. The concentration of the impact of economic growth on the spreads of revolving credit and consumer loans suggests that banks assess costumers of these loan types as those with more room to improve their repayment ability in periods of economic bonanza.

The negative coefficient of *SttOwn* suggests that state-owned banks tend to charge lower spreads in revolving credit loans. This result is also in line with previous literature claiming that state-owned banks are more subject to political pressures to reduce spreads (Demirguç-Kunt et al., 2004). The lack of statistical significance of *SttOwn x Cons* is indicative that consumer loan spreads are not influenced by this variable. The resulting sum of the *SttOwn* and *SttOwn x Payroll* coefficients, in turn, suggests that the impact of the state ownership of the bank on the payroll-linked loan spread is positive. A possible explanation for the difference in the impact of this variable across the spreads of the three categories is the high average of revolving credit spreads. This makes this loan type the one that offers more room for state-owned banks to give in to political pressure to reduce spreads. Conversely, this reduction seems to be compensated by an increase in the spread of payroll-linked loans. As the spreads charged in the latter category of loan are considerably lower, there is a tendency for less political pressure to reduce the spreads in this loan type in the case of state-owned banks.

These results support the main hypothesis of this study, that is, the impact of banking spread determinants on spread formation differs according to the loan category. Take, for example, the impact of the interbank interest rate (*Selic*). This impact is higher on the spread of revolving credit loans than on the spread of consumer loans and of payroll-linked loans. This is explained by the portfolio effect demonstrated by Allen (1988), which allows banks to better manage their inventory risk exposure by controlling relative rate spreads across product types. One corollary of this reasoning is that riskier loan categories should be more impacted by some of the bank's costs to compensate for their higher risk. Among the three categories, revolving credit loans is the riskiest: costumers can withdraw all the funds (or part of them) available in a deposit account whenever they want, and there is no scheduled date for paying it back. As soon as the debt is paid, the costumer can withdraw it again. Consumer loans and payroll-linked loans, on the other hand, have well-defined monthly installments, which makes the repayment more predictable. There is also a well-defined date for making the funds available to the client. Payroll-linked loans are the least risky category among the three because, in addition to the more predictable withdrawals and repayments, instalments are directly debited in the civil servant's monthly paycheck, diminishing default risk. The most part of interbank interest rate costs is passed on to borrowers of the riskiest loan category (revolving credit), a small part is passed on to the middle risky category (consumer loans) and the smallest part is passed on to borrowers of the least risky category (payroll-linked loans). *MktRsk* and *ImpInt* are other variables corroborating the idea that banks manage their inventory risk exposure by controlling spreads across loan categories. This result is in line with the portfolio effect theory.

The model is well specified according to the diagnostic tests on the estimated residuals for dynamic panel data. According to the Arellano-Bond AR(2) test, there is no evidence of second order autocorrelation in the residuals at the standard 5% significance level. The Hansen test of over-identifying restrictions, which tests the overall validity of the instruments, indicates that the set of instruments is orthogonal to estimated residuals.

6 Robustness check

To alleviate concerns regarding the non-stationarity of the panel and time series used in the estimation, the estimates obtained through difference GMM are also presented, in addition to the results of system GMM, which relies on the mean stationarity assumption. The dummy variable *SttOwn* was naturally dropped from the estimation using difference GMM due to the limitation of using only first differences in this method. The change in the estimated model and in the method of estimation brought some changes to the results. Table 7 presents these results. Differently from system GMM, the coefficient of *CrtRsk* is positive and statistically significant, suggesting that the higher the bank's credit risk, the higher the spread of revolving credit loans. This result is in line with previous studies that found a positive relationship between NIM and credit risk (Entrop et al., 2015; Jarmuzek & Lybek, 2020). *IntRsk* has a statistically significant coefficient in this estimation, whereas it was not significant in system GMM. The positive sign suggests that banks pass on to borrowers of revolving credit loans the volatility of the market interest rates. This result is also supported by previous studies that use NIM in lieu of actual interest rate spreads (Entrop et al., 2015; Jarmuzek & Lybek, 2020; López-Espinosa et al., 2011).

RskAvs, *Infl*, and *MktSh* are not statistically significant under this estimation method. One other difference is that the opportunity cost of holding reserves has a negative estimated relationship with the spread of consumer loans and a positive—though small—relationship with the spread of payroll-linked loans. The differences in the results of system and difference GMM are not unusual, given the changes in the estimated dynamic model, due to the impossibility of using the time invariant variable *SttOwn* and its interaction terms. These variables proved to be relevant for explaining the behavior of the spreads of revolving credit loans and payroll-linked loans, respectively, in system GMM.

Table 7
Determinants of Interest Rate Spreads – Estimation Results (Difference GMM)

Variable	Coefficient (p-value)
$Spread_{i,t-1}$	0.58 (0.004)
$Spread_{i,t-1} \times Cons_i$	-0.13 (0.649)
$CrtRsk_{it}$	3.21 (0.063)
$LqtRsk_{it}$	-0.09 (0.854)
$RskAvs_{it}$	6.99 (0.237)
$ImpInt_{it}$	8.09 (0.267)
$ImpInt_{it} \times Cons_i$	-8.74 (0.231)
$ImpInt_{it} \times Payroll_i$	-9.19 (0.277)
$OppRsv_{it}$	-19.36 (0.025)
$OppRsv_{it} \times Cons_i$	18.14 (0.026)
$OppRsv_{it} \times Payroll_i$	19.85 (0.021)
$MktSh_{it}$	6.11 (0.351)
$MktSh_{it} \times Cons_i$	-4.35 (0.508)
$MktSh_{it} \times Payroll_i$	-3.82 (0.565)
$Infl_t$	1.33 (0.625)
$Selic_t$	9.25 (0.000)
$Selic_t \times Cons_i$	-7.30 (0.001)
$Selic_t \times Payroll_i$	-9.12 (0.000)
$IntRsk_t$	1.97 (0.064)
$GDPg_t$	13.32 (0.000)

$GDPg_t \times Cons_i$	-10.41 (0.000)
$GDPg_t \times Payroll_i$	-13.10 (0.000)

The two-step Difference GMM estimators with robust errors is used. *p*-values in parenthesis. Number of observations: 663. Wald chi^2 *p*-value: 0.000. Arellano-Bond AR (1) *p*-value = .066; Arellano-Bond AR (2) *p*-value = .159. Hansen overidentification test: *p*-value = .001. GMM set of instruments: 2rd lag of spread. Total number of instruments used: 36. Check table 1 for description of variables.

Some similarities remain. The first is that the lagged dependent variable also explains a high percentage of the behavior of revolving credit spreads, although its coefficient is substantially smaller than the one estimated using system GMM. In this case, only 58% of the current spread of revolving credit loans is explained by the last period spread of this loan category. The results obtained with difference GMM also suggest that the market interest rate influences the spread of the three loan categories. Again, the influence is positive on the spread of revolving credit loans, smaller but still positive on the spread of consumer loans and roughly null (but still positive) on the spread of payroll-linked loans. Under difference GMM, economic growth is also positively related to the spreads of both revolving credit and—to a lesser extent—consumer loans, but its influence on the spread of payroll-linked loans is roughly null.

We also run a GLS regression, as one other robustness check of the hypothesis that the impact of spread determinants differs according to the loan category. It was estimated by random effects because the Hausman test exhibited a *p-value* = .8553, not rejecting the null hypothesis of random effects. Table 8 presents the results. There are more similarities than differences between random effects and system GMM estimates. The random effects estimate confirms the inertial effect of the revolving credit spread and the lack of an inertial effect of the consumer loan spread. There is no statistical significance in the *CrtRsk*, *LqtRsk*, and *IntRsk* variables. Market interbank rate and economic growth influence the spread of all three loan categories differently. Implicit interest payments seem to positively influence the revolving credit spread, but not the spreads of the other two loan categories (in fact, there is some influence on payroll-linked loans spread, but when adding the coefficients of *ImpInt* and *ImpInt x Payroll*, the resulting sum is approximately zero). State-ownership appears to decrease the revolving credit spread, which is offset by the increase in payroll-linked loans spread. Apparently, the spread of consumer loans is not influenced by state-ownership of the bank. Conversely, the differences between estimates obtained by random effects and by system GMM are few. There is no statistical significance in the *RksAvs* coefficient. The same negative relationship between the opportunity cost of holding reserves and revolving credit spreads is obtained with random effects estimation. However, the apparent offsetting effect verified in system GMM between revolving credit and consumer loans spreads is absent in random effects estimation. Robust standard errors are computed in the variance-covariance matrix of estimators presented in Table 8. These standard errors are identical to those obtained by clustering on the panel variable, yielding an estimator of the variance-covariance matrix that is robust to cross-sectional heteroskedasticity and within-panel (serial) correlation (Wooldridge, 2020).

Table 8

Determinants of Interest Rate Spreads – Estimation Results (Random Effects)

Variable	Coefficient (p-value)
$Spread_{it-1}$	0.88 (0.000)
$Spread_{it-1} \times Cons_i$	0.05 (0.102)
$CrtRsk_{it}$	0.86 (0.257)
$LqtRsk_{it}$	0.01 (0.922)
$RskAvs_{it}$	1.17 (0.455)
$ImpInt_{it}$	6.50 (0.001)
$ImpInt_{it}x\ Cons_i$	-3.89 (0.177)
$ImpInt_{it}x\ Payroll_i$	-6.56 (0.002)
$OppRsv_{it}$	-9.22 (0.000)
$OppRsv_{it}x\ Cons_i$	8.48 (0.001)
$OppRsv_{it}xPayroll_i$	9.29 (0.000)
$MktSh_{it}$	0.60 (0.112)
$MktSh_{it}xCons_i$	-.34 (0.242)
$MktSh_{it}xPayroll_i$	-.39 (0.143)
$Infl_t$	3.51 (0.008)
$Selic_t$	4.99 (0.000)
$Selic_t \times Cons_i$	-3.77 (0.001)
$Selic_t \times Payroll_i$	-5.04 (0.000)
$IntRsk_t$	-1.04 (0.569)

$GDPg_t$	7.16 (0.000)
$GDPg_t \times Cons_i$	-2.46 (0.536)
$GDPg_t \times Payroll_i$	-6.87 (0.000)
$SttOwn_i$	-18.94 (0.000)
$SttOwn_i \times Cons_i$	11.04 (0.265)
$SttOwn_i \times Payroll_i$	22.99 (0.000)
$Constant$	-24.57 (0.005)

Number of observations: 702. Wald chi^2. *p-value*: 0.0000. VCE estimators robust to cross-sectional heteroskedasticity and within-panel (serial) correlation are used. *p*-values in parenthesis. Check table 1 for description of variables.

The differences across random effects, difference GMM and system GMM estimation results do not appear to compromise the overall conclusion of the study. The evidence of differentiated impact given by the interaction terms of the variables *OppRsv*, *Selic*, and *GDPg*, present under all three approaches, adds to the robustness of our overall conclusions, in support of the main hypothesis of this study.

7 Concluding Remarks

Previous studies on banking spreads use one single interest margin per bank to measure the impact of its determinants, usually the net interest margin (NIM) derived from accounting statements. The present study stems from the general conjecture that the attributes that influence the behavior of banking spreads can have a specific impact according to the loan category. Therefore, when studying the behavior of banking spreads, the diversity of interest rates existing in a bank's loan portfolio should be considered.

Bearing in mind the theoretical model proposed by Ho and Saunders (1981) and some of its extensions, this paper analyses the impact of the determinants of banking spread for three types of personal loans in the context of the Brazilian banking sector: revolving credit, consumer loans, and payroll-linked loans to civil servants. In particular, the paper assesses the hypothesis derived from the study by Allen (1988), who extended the dealership model incorporating the loan heterogeneity in banks' portfolios. The Author demonstrated that banks diversify their risk inventory exposure by controlling the relative rate spreads across product types. This suggests that the influence of the determinants of banking spreads varies according to the loan category.

The empirical results confirmed the expected differentiated effect of some determinants on the spread of the three distinct loan categories analyzed. Under system GMM estimation, the marginal effects of the market interest rate, and economic growth on the spreads of revolving credit, consumer loans, and payroll-linked loans differ significantly among the three. In addition, implicit interest payments and the bank's market share have significant marginal impact on the spread of revolving credit, but not on the spreads of the other two categories. Also, the marginal effect of the opportunity cost of holding reserves on the spread of revolving credit differs significantly from the corresponding marginal effect on the spread of consumer loans, and it does not influence the spread of payroll-linked loans at all. Similarly, the banks' state-ownership influence on the spread of revolving credit differs significantly from the corresponding marginal effect on the spread of payroll-linked loans, and it does not influence the spread of consumer loans. Generally, the covariates with statistical significance in system GMM and in the other two estimations used as robustness checks confirmed the expected relationships with banking spreads. Nevertheless, the lack of statistical significance in some variables is suggestive of how banking spreads can behave differently when computed using actual interest rates. The vector of microeconomic variables is computed from accounting data, which have a hindsight profile, while spreads computed by actual interest rates (instead of NIM) have a foresight behavior. This may explain the lack of statistical significance of some of the bank-specific covariates.

The study of the determinants of spreads should consider the heterogeneity existing in a bank's loan portfolio, especially in a context of high spreads like that of the Brazilian banking sector. Data gathered from financial statements only provide averages of the spreads charged in many loan categories, which naturally limits the investigation and precludes the design of policies addressing specific characteristics of credit lines. Central banks and governments should observe the composition of banks' loans portfolio when writing their regulations. Policies could be designed and implemented specifically targeting loan categories sensitive to certain factors.

For instance, in view of the evidence that implicit interest payments are passed on to customers of revolving credit, but not to customers of the two other loan categories, the Central Bank could allow banks to charge revolving credit the same fees that are charged on consumer and payroll-linked loans. Other example concerns the opportunity cost of holding reserves. Given the cross-subsidy effect between revolving credit and consumer loans, the Central Bank could waiver a rediscount rate in cases where banks have unforeseen liquidity needs due to unexpected withdrawals on revolving credit. This could reduce the need to hold bank reserves on hand and, consequently, the need for subsidy across lending categories. To reduce the influence of bank's market power on the spread of revolving credit, regulators could encourage the provision of revolving credit lines by a greater number of financial institutions. The competition would be levelled in this way, as in the case of consumer and payroll-linked loans, whose spreads are not influenced by the bank's market power. Given that the market interest rate impacts differently the spread of different loan categories, regulative authorities could establish some cap to modifications in the spreads of the categories where this relationship is most relevant so as to curb excessive spreads in these categories whenever the basic interest rate is increased. In periods of economic boom, regulative authorities could reduce reserve requirements in exchange for lowering revolving credit spreads, since this is the type of loan whose spreads banks are most likely to increase in periods of economic growth. Finally, given that political pressure reduces the high spreads of revolving credit, policymakers can assess the relevance of influencing the level of spread charged by private banks competing in specific lending categories, through the rates adopted by state-owned banks.

In addition to providing evidence for the hypothesis of differentiated impact of spread determinants according to the loan type, this study contributes to the related literature offering evidence of the factors that influence the spread of three specific loan categories for individuals. Particularly, it shows that: i. revolving credit spreads are driven mainly by the spread of the previous period, bank's risk aversion, implicit interest payments, opportunity cost of holding reserves, the bank's market share, the inflation rate, market interest rate, economic growth, and state-ownership of the bank; ii. consumer loans spreads are driven by the opportunity cost of holding reserves and market interest rate; iii. payroll-linked loans spreads are also driven by the market interest rate, GDP growth, and the bank's state-ownership. One other contribution to the literature regards the way spreads should be computed when investigating their determinants. The prominence of macroeconomic variables like *Selic* and *GDPg* in explaining the spread behavior is more in line with the study by Afanasieff *et al*. (2002) than with the study by Almeida and Divino (2015). Both studies investigate the spreads in Brazil, but the former uses actual interest rates—like the present study—in the computation of banking spread, whereas the latter uses NIM as a proxy for the banking spread. In the study by Afanasieff *et al*. (2002) —as in here—macroeconomic attributes have more prominence than microeconomic ones in explaining the behavior of the spread, while in the study by Almeida and Divino (2015) the opposite occurs. This study confirms that different results can be obtained according to the way spreads are computed, and regulators and scholars should keep this in mind.

Naturally, this study is not without limitations. The first limitation is related to the restriction of the sample to Brazil. Unfortunately, it was not possible to include other countries in the study, given that the disclosure of interest rates charged per loan category is not available on any international database. The second limitation regards the number of banks and loan categories analyzed, which is explained by the availability of data. Although the Central Bank of Brazil collects data related to interest rates charged on personal loans by a greater number of financial institutions on personal loans, most of the smaller banks do not report data for most of the loan categories. To obtain a completely balanced panel of interest rate spreads, the banks without observations in one or more of the nineteen semesters comprising the timeline were dropped from the sample. Loan categories for which the remaining banks did not report interest rates for all 19 semesters of the sample were also removed. In addition, the simple average used in the computation of the dependent variable—due to the unavailability of public data on loan proceeds to compute a weighted average—may raise some concerns related to biases. Due to multicollinearity issues and the necessity to limit the number of instruments used, we did not test the hypothesis of differentiated impact on the spread according to the loan category for some determinants that proved relevant for explaining the behavior of the spreads of revolving credit loans, like risk aversion and inflation. These are limitations that, in any event, may encourage subsequent research on the determinants of banking spreads.

8 References

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APPENDIX

Correlation matrix – dependent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
CrtRsk (1)	1.00																	
CrtRsk x Cons (2)	0.23	1.00																
CrtRsk x Payroll (3)	0.23	-0.42	1.00															
LqtRsk (4)	0.11	0.02	0.02	1.00														
LqtRsk x Cons (5)	0.03	0.82	-0.40	0.28	1.00													
LqtRsk x Payroll (6)	0.03	-0.40	0.82	0.28	-0.38	1.00												
RskAvs (7)	-0.00	-0.00	-0.00	-0.29	-0.08	-0.08	1.00											
RskAvs x Cons (8)	-0.00	0.84	-0.42	-0.07	0.75	-0.40	0.23	1.00										
RskAvs x Payroll (9)	-0.00	-0.42	0.84	-0.07	-0.40	0.75	0.23	-0.42	1.00									
OprCst (10)	-0.23	-0.05	-0.05	-0.26	-0.07	-0.07	0.37	0.09	0.09	1.00								
OprCst x Cons (11)	-0.08	0.67	-0.36	-0.09	0.62	-0.35	0.13	0.82	-0.37	0.35	1.00							
OprCst x Payroll (12)	-0.08	-0.36	0.67	-0.09	-0.35	0.62	0.13	-0.37	0.82	0.35	-0.32	1.00						
ImpInt (13)	-0.05	-0.01	-0.01	-0.22	-0.06	-0.06	0.29	0.07	0.07	0.89	0.30	0.30	1.00					
ImpInt x Cons (14)	-0.03	0.32	-0.17	-0.12	0.23	-0.16	0.15	0.45	-0.17	0.46	0.78	-0.15	0.54	1.00				
ImpInt x Payroll (15)	-0.03	-0.17	0.32	-0.12	-0.16	0.23	0.15	-0.17	0.44	0.46	-0.15	0.78	0.54	-0.06	1.00			
OppRsv (16)	0.14	0.03	0.03	-0.05	-0.01	-0.01	0.12	0.03	0.03	0.60	0.21	0.21	0.65	0.35	0.35	1.00		
OppRsv x Cons (17)	0.07	0.60	-0.28	-0.02	0.51	-0.26	0.06	0.59	-0.28	0.28	0.77	-0.24	0.30	0.70	-0.11	0.46	1.00	
OppRsv x Payroll (18)	0.07	-0.28	0.60	-0.02	-0.26	0.51	0.06	-0.28	0.59	0.28	-0.24	0.77	0.30	-0.11	0.70	0.46	-0.18	1.00
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(16)	(17)	(18)	(19)	(20)	(21)

Infl (19)	-0.14	-0.03	-0.03	-0.10	-0.03	-0.03	-0.04	-0.01	-0.01	-0.04	-0.01	-0.01	-0.02	-0.01	-0.01	-0.00	-0.00	-0.00
Infl x Cons (20)	0.04	0.75	-0.39	-0.03	0.72	-0.37	-0.01	0.77	-0.39	-0.01	0.67	-0.34	-0.01	0.31	-0.16	-0.00	0.51	-0.26
Inflx x Payroll (21)	0.04	-0.39	0.75	-0.03	-0.37	0.72	-0.01	-0.39	0.77	-0.01	-0.34	0.67	-0.01	-0.16	0.31	-0.00	-0.26	0.51
Selic (22)	0.13	0.03	0.03	-0.00	-0.00	-0.00	-0.05	-0.01	-0.01	0.04	0.01	0.02	0.04	0.02	0.02	-0.09	0.04	-0.04
Selic x Cons (23)	0.03	0.83	-0.40	-0.00	0.77	-0.38	-0.02	0.80	-0.40	0.01	0.71	-0.35	0.01	0.35	-0.16	-0.02	0.50	-0.26
Selic x Payroll (24)	0.03	-0.40	0.83	-0.00	-0.38	0.77	-0.02	-0.40	0.80	0.01	-0.35	0.71	0.01	-0.16	0.35	-0.02	-0.26	0.50
IntRsk (25)	0.00	0.00	0.00	0.01	0.00	0.00	0.03	0.01	0.01	-0.00	-0.00	-0.00	0.05	0.03	0.03	-0.02	-0.01	-0.01
IntRsk x Cons (26)	0.00	0.81	-0.41	0.00	0.78	-0.39	0.01	0.82	-0.41	-0.00	0.71	-0.35	0.01	0.35	-0.17	-0.01	0.53	-0.27
IntRsk x Payroll (27)	0.00	-0.41	0.81	0.00	-0.39	0.78	0.01	-0.41	0.82	-0.00	-0.35	0.71	0.01	-0.17	0.35	-0.01	-0.27	0.53
GDPg (28)	-0.12	-0.03	-0.03	-0.07	-0.02	-0.02	0.05	0.01	0.01	-0.01	-0.00	-0.00	0.05	0.03	0.03	-0.05	-0.02	-0.02
GDPg x Cons (29)	-0.07	-0.01	-0.03	-0.04	0.00	-0.02	0.03	0.06	-0.02	-0.00	0.03	-0.02	0.03	0.06	-0.01	-0.03	-0.01	-0.01
GDPg x Payroll (30)	-0.07	-0.02	0.00	-0.04	-0.02	0.00	0.03	-0.02	0.06	-0.00	-0.02	0.03	0.03	-0.01	0.06	-0.03	-0.01	-0.01
MktSh (31)	-0.02	-0.00	-0.00	-0.01	-0.00	-0.00	-0.53	-0.12	-0.12	-0.47	-0.17	-0.17	-0.46	-0.25	-0.25	-0.20	-0.09	-0.09
MktSh x Cons (32)	-0.01	0.45	-0.23	-0.00	0.43	-0.22	-0.27	0.28	-0.23	-0.24	0.15	-0.20	-0.23	-0.19	-0.09	-0.10	0.16	-0.15
MktSh x Payroll (33)	-0.01	-0.23	0.46	-0.00	-0.22	0.43	-0.27	-0.23	0.28	-0.24	-0.20	0.15	-0.23	-0.09	-0.19	-0.10	-0.15	0.16
SttOwn (34)	-0.58	-0.14	-0.13	-0.18	-0.05	-0.05	-0.20	-0.05	-0.05	0.32	0.11	0.11	0.21	0.11	0.11	-0.04	-0.02	-0.02
SttOwn x Cons (35)	-0.25	0.43	-0.30	-0.08	0.51	-0.29	-0.09	0.55	-0.30	0.14	0.67	-0.26	0.09	0.39	-0.12	-0.02	0.38	-0.20
SttOwn x Payroll (36)	-0.25	-0.30	0.43	-0.08	-0.29	0.51	-0.09	-0.30	0.55	0.14	-0.26	0.67	0.09	-0.12	0.39	-0.02	-0.20	0.38
$Selic_{t-1}$ x Cons (37)	0.01	0.49	-0.24	-0.04	0.43	-0.23	0.21	0.63	-0.24	-0.01	0.41	-0.21	0.03	0.24	-0.10	0.02	0.34	-0.16
$Selic_{t-1}$ x Payroll (38)	-0.01	-0.44	0.87	0.01	-0.42	0.85	0.04	-0.44	0.91	0.04	-0.38	0.81	0.03	-0.18	0.41	0.02	-0.29	0.61
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)

Infl (19)	1.00																	
Infl x Cons (20)	0.30	1.00																
Inflx x Payroll (21)	0.30	-0.36	1.00															
Selic (22)	0.26	0.08	0.08	1.00														
Selic x Cons (23)	0.07	0.81	-0.37	0.28	1.00													
Selic x Payroll (24)	0.07	-0.37	0.81	0.28	-0.39	1.00												
IntRsk (25)	0.05	0.02	0.02	-0.22	-0.06	-0.06	1.00											
IntRsk x Cons (26)	0.01	0.77	-0.38	-0.06	0.73	-0.39	0.27	1.00										
IntRsk x Payroll (27)	0.01	-0.38	0.77	-0.06	-0.39	0.73	0.27	-0.39	1.00									
GDPg (28)	-0.07	-0.02	-0.02	-0.39	-0.11	-0.11	0.22	0.06	0.06	1.00								
GDPg x Cons (29)	-0.04	-0.00	-0.02	-0.22	-0.15	-0.02	0.13	0.14	-0.02	0.58	1.00							
GDPg x Payroll (30)	-0.04	-0.02	-0.00	-0.22	-0.02	-0.15	0.13	-0.02	0.14	0.58	-0.00	1.00						
MktSh (31)	-0.01	-0.00	-0.00	-0.01	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.00	-0.00	1.00					
MktSh x Cons (32)	-0.01	0.42	-0.21	-0.00	0.44	-0.22	0.00	0.44	-0.22	-0.00	0.02	-0.01	0.50	1.00				
MktSh x Payroll (33)	-0.01	-0.21	0.42	-0.00	-0.22	0.44	0.00	-0.22	0.44	-0.00	-0.01	0.02	0.50	-0.13	1.00			
SttOwn (34)	-0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	-0.00	0.00	0.00	0.14	0.07	07	1.00		
SttOwn x Cons (35)	0.00	0.56	-0.28	-0.00	0.58	-0.29	0.00	0.59	-0.29	-0.00	0.03	-0.01	0.06	0.42	-0.17	0.43	1.00	
SttOwn x Payroll (36)	0.00	-0.28	0.56	-0.00	-0.29	0.58	0.00	-0.29	0.59	-0.00	-0.01	0.03	0.06	-0.17	0.42	0.43	-0.22	1.00
Selic$_{t-1}$ x Cons (37)	-0.01	0.44	-0.23	0.02	0.48	-0.23	0.01	0.48	-0.23	-0.01	-0.00	-0.01	-0.09	0.13	-0.13	-0.17	0.12	-0.17
Selic$_{t-1}$ x Payroll (38)	-0.04	-0.41	0.79	-0.04	-0.42	0.81	0.03	-0.43	0.89	0.03	-0.02	0.08	-0.04	-0.24	0.42	-0.02	0.32	0.62
	(37)	(38)																

$Selic_{t-1}$ x Cons (37)	1.00																	
$Selic_{t-1}$ x Payroll (38)	-0.25	1.00																