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Lending rate sensitivity to monetary policy: a bank level empirical analysis

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Abstract

Purpose – This paper evaluates how the monetary policy rate influences bank lending rates in Peru, focusing on various loan types from September 2010 to August 2022.
Design/methodology/approach – We utilize the Bai and Perron (1998, 2003) methodology to account for structural changes in the pass-through effect of monetary policy on lending rates.
Findings – Findings indicate a heterogeneous impact of monetary policy on lending rates, with larger effects during significant rate changes and heightened sensitivity post-2019 due to COVID-19.
Originality/value – This study is the first to investigate the effects of monetary policy on interest rates using segment and bank level data in Peru.

Keywords Interest rates, Pass-through, Structural change, Peruvian economy
Paper type Research article

1. Introduction

Banks play a critical role in the transmission of monetary policy, particularly through lending rates, which are crucial for central banks to achieve policy objectives (Altavilla *et al.*, 2020). After the Great Financial Crisis, developed countries faced diminished effectiveness of monetary policy due to either low interest rates (Eggertsson and Woodford, 2003) or reduced volatility, a condition that continued until the COVID-19 pandemic. This paper revisits the impact of monetary policy rates (MPR) on lending rates to firms using bank-level data from Peru from November 2010 to August 2022, accounting for non-linearities and structural breaks.

The Peruvian banking sector, characterized by high market concentration, provides an interesting case study. According to the 2022 Global Financial Development Database, Peru's banking market is one of the most concentrated in the region, with the top three commercial banks holding 71.6% of total assets, compared to Brazil's 73.1%. This concentration extends to the five largest banks, averaging 90% since 2003.

Market concentration varies by credit type. The Peruvian financial sector, comprising banks, cajas municipales and cajas rurales, shows differing concentration levels measured by the Herfindahl–Hirschman Index (HHI). The small enterprise segment is least concentrated (HHI of 0.12), while large enterprises and microfinance are moderately concentrated (HHIs of 0.22 and 0.18, respectively). Corporate and medium enterprise segments are highly concentrated (HHIs of 0.25 and 0.27, respectively).

Analyzing the disparity between lending and borrowing rates, Peru ranks second only to Brazil, with an average lending–deposit spread of 13% from 2010 to 2020, compared to a regional median of 6.6%. Elevated spreads suggest significant market power, potentially undermining monetary policy efficacy (Brock and Franken, 2003; Afanasieff *et al.*, 2002).

Our analysis reveals a time-varying relationship between MPRs and lending rates, with structural breaks indicating regime changes. These changes were triggered by reductions in the

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Central Bank reference rate around 2017 and a shift in mid to late 2019 during a period of looser monetary policy and pre-pandemic volatility. Post-2019, the interbank rate's impact on final interest rates has increased, although heterogeneously across segments. Small enterprise and microenterprise segments exhibit higher pass-through (PT) coefficients in the long run, while the corporate segment shows lower PT, influenced by interest rate volatility post-2019. After controlling for dummy variables during 2020, the results show lower PT rates in loans provided to small enterprises and micro enterprises.

The document is structured as follows: Section 2 provides a literature review and briefly describes the Peruvian bank credit market; Section 3 details the methodology; Section 4 discusses the data and presents the main findings, being complemented with a simulation study; Section 5 covers robustness checks; Section 7 concludes the study.

2. Literature review

The effectiveness of monetary policy relies heavily on the pricing decisions made by financial institutions, particularly regarding lending rates. While numerous papers address this issue, most focus on the impact of monetary policy on lending rates at an aggregate level. Existing literature on this topic can be categorized into three main strands: The first strand, influenced by industrial organization theory, suggests that market structure primarily accounts for the stickiness of lending rates. Factors such as market concentration, competition intensity, entry barriers, the presence of state-owned financial institutions and the sophistication of financial markets are identified as key determinants of the transmission of MPRs through the banking channel. Examples include Pelzman (1969), Cottarelli and Koruelis (1994), van Leuvensteijn *et al*. (2013) and Sääskilahti (2016).

The second strand measures the influence of monetary policy on lending rates and its interaction with the financial institutions' own characteristics. In this literature, the PT is affected by the size of the institution, type of funding and liability structures, banks' risk appetite and share of non-performing loans (NPLs), among others. This represents one of the most abundant strands, both in developed markets; see for example, Mueller-Spahn (2008), Banerjee *et al*. (2013), Holton and Rodriguez (2015), Illes *et al*. (2015), Altavilla *et al*. (2020), Holland *et al*. (2020), Blot and Labondance (2021) and in emerging markets (see Berstein and Fuentes, 2004; Curti, 2010; Alencar, 2011; Bennouna, 2019) [1].

Finally, the third category accounts for the fluctuations in the PT due to information asymmetry between lenders and financial institutions. For instance, Winker (1999) explains the rigidity of interest rates because of credit rationing caused by adverse selection and switching costs.

From a data point of view, some studies employ aggregate data, while others utilize bank-level data. However, papers relying on aggregate data face a significant limitation: the heterogeneous nature of pricing decisions made by banks can result in various PT rates across different segments. Conversely, research utilizing bank-level data, particularly in developed countries, is abundant (see for example, Mueller-Spahn, 2008; Bennouna, 2019 for reviews) and is relatively scarce in emerging countries, including Latin America; see Berstein and Fuentes (2004), Alencar (2011), Ashraf *et al*. (2021).

The literature above also highlights certain limitations associated with the methodologies employed. Specifically, many studies utilizing bank-level data rely on static or dynamic panel specifications based on the Arellano and Bond (1991). However, in macroeconomic analyses employing aggregate data, it is widely acknowledged that the PT dynamic often entails a significant non-linear component. Threshold analyses based on co-integration techniques have been utilized, both with bank-level data (for instance, Lago and Salas (2005) and product-level data (Rocha, 2012; Gregor and Mekecky, 2018)). Moreover, the time-series literature has explored time-varying parameters to measure PT effects at the aggregate level. Yet, to the best of our knowledge, none of these methodologies have been applied within the context of a heterogeneous sample of banks. Altavilla *et al*. (2020)

address these challenges by employing a two-step cross-sectional VAR, yielding time-varying estimates of PT effects. However, they do not derive time-varying parameters for other macroeconomic variables influencing lending rates, nor do they identify different responses among banks.

Another particularly significant study is that of Humala (2005). The author assesses the PT of monetary policy in which the sample is affected by two crises: the 1994 Mexican crisis and the collapse of the convertibility system in Argentina in 2001. The obtained PT coefficients are markedly higher than those found in the rest of the literature. To address this issue, the author introduces dummy variables that reduce the PT coefficients.

In the Peruvian case, the literature exhibits analogous constraints encountered in other national contexts. Lahura (2005) analyzes the impact of the reference rate on aggregate deposit and lending rates [2] by using co-integration techniques for the 1995–2004 period, finding an incomplete PT which increased after the Peruvian central bank adopted an inflation targeting (IT) regime. Moreover, Lahura identifies asymmetric effects stemming from fluctuations in the reference rate. A different approach is proposed by Rostagno and Castillo (2010), who introduce an asymmetric co-integration model to explain the PT effect. They analyze both lending and deposit rates. For lending rates, they consider commercial and microfinance rates for various maturities, credit cards and mortgages. However, their study does not utilize bank-level data. The authors find evidence of asymmetric effects and discard the existence of co-integration between the reference rate and credit card, mortgage and microfinance loan rates. In a subsequent study, Mejia (2019) examines the same issue from a macroeconomic perspective utilizing a structural VAR. The findings reveal an important PT within 24 months, obtaining an elasticity of 3.04. Conversely, a reduced PT is observed for cajas municipales. This observed difference in PT may be attributed to different cost structures within the latter segment, which could impede their capacity to respond to changes in the reference rate.

In a departure from prior literature, Chumpitaz (2007) and Cermeño *et al*. (2016) examined the influence of the reference rate on both short- and long-term aggregate lending rates utilizing bank-level data. The former study employs a panel co-integration approach, yielding results consistent with existing literature, while introducing NPLs as an explanatory variable. This addition only impacts PT coefficients in the short run, but it does not affect long-run PTs. Conversely, Cermeño *et al*. (2016), using panel data, found a short-run effect of the reference rate on lending rates that intensifies with the term of the loan. However, the long-run effect reveals a weaker PT. Furthermore, Rivera (2018) employs panel co-integration to assess the impact of the MPR on short-term commercial loans, revealing an important degree of stickiness in lending rates.

Departing from the existing literature, we use bank-level data and introduce a non-linear framework, which accounts for different regimes to determine the relationship between bank lending rates and the MPR. Furthermore, diverging from prior studies, we analyze the impact of the MPR on various lending rates across distinct segments, each characterized by heterogeneous attributes.

2.1 The Peruvian bank credit market

Since the early 1990s, the Peruvian financial landscape has experienced notable transformations characterized by the introduction of novel financial instruments and services and augmented regulatory measures which fostered financial resilience (Poggi *et al*., 2015). This period was also characterized by economic reforms and the emergence of novel entities such as microfinance institutions and non-bank financial intermediaries. However, over the course of the past 15 years, the number of commercial banks has been relatively constant.

Those reforms implied a convergence in deposit rates to international levels (Humala, 2005). However, in the case of lending rates, loans made to large corporate clients, who often have the option to finance themselves by raising capital or by accessing foreign markets, are mostly at or very close to, international levels. On the other hand, interest rates on other types of loans show a substantial degree of heterogeneity and in some cases are well above international rates.

The credit market has also been influenced by the monetary policy implemented by the Central Bank which, since 2002 implemented an IT regime; see Armas *et al.* (2014). The implementation of the IT regime has increased the magnitude of the PT effect from the MPR to aggregate lending rates, as mentioned by Lahura (2005).

The Peruvian financial system has seen relative stability until the COVID-19 pandemic. Conversely, the MPR has had some significant fluctuations before that, mainly during the 2016–17 period. In April 2020, the government implemented a backed loans program, called Reactiva Peru and FAE Mype [3]. The Reactiva program's main objective was to ensure continuity in the payment chain by providing guarantees up to 98% to micro, small, medium and large companies so that they can access short-term loans. The Peruvian government served as a guarantor of the credits issued by financial institutions, by a total amount of 60,000 million Soles, equivalent to 8% of Peru's GDP at the time. FAE Mype operated in a similar fashion but was directed only at micro and small enterprises. Given that the Peruvian government served as a guarantor of all loans, the rates were substantially low.

3. Method

In this section, we will propose a simple theoretical model in which an equilibrium relationship is established between the interest rate charged by banks, the MPR and portfolio risk. This will be followed by the formulation of the empirical specification, which will later be used to estimate various models.

3.1 A simple model

Following Freixas and Rochet (2008) and Winker (1999), this section presents a model that relates pricing decisions of financial institutions to MPR, which will serve as a basis for the empirical analysis, as well as some explanations for the conclusions drawn from it.

First, we assume imperfect competition in the banking sector, as well as asymmetric information, which leads to adverse selection and moral hazard problems (see for example Winker, 1999; Diamond and Dybvig, 1983; Besanko and Thakor, 1987). We combine these two points by assuming that banks make a two-stage decision, considering both the long-term equilibrium and the short-term behavior that will lead them to this condition.

We assume a Monti-Klein model for the long term, where a monopolistic bank faces a negatively sloped demand for its loans $L(r_L)$ and a supply of deposits with positive slope $D(r_D)$, capturing the fact that banks have some monopolistic power and that loans are risky assets. The firm's decision variables are the volume of loans (L) and deposits (D). Bank k maximizes the following utility function:

$$\pi_k = \left[\int_{-\infty}^{\infty} \min[i(L), \widetilde{y}_k] f\left(\widetilde{y}_k\right) d\widetilde{y}\right] L_k - rL_k + (MPR - r_{D,k})D_k + C_k(D_k, L_k) \qquad (1)$$

Where $\widetilde{y}$ represents the threshold yield, which is the minimum return on investment that the bank requires to compensate for the default risk. Thus, if the expected return on a loan is below the threshold yield, the bank will not grant the loan. On the other hand, *MPR* is the monetary policy rate, i is the interest rate associated with loans, r_D is the interest rate associated with deposits and C_k represents the costs associated with financial intermediation.

From the maximization of equation (1), the following expression for the equilibrium loan interest rate is derived, where p is the probability of default and $\varepsilon_{L,k}$ is the demand elasticity of loans for bank k.

$$i_k = \frac{\varepsilon_{L,k}}{(1 - \varepsilon_{L,k})p}\left(MPR + C'_{L,k} - \widetilde{y}_{c,k}\right) \tag{2}$$

As seen in equation (2), the interest rate depends positively on the MPR and it is inversely related to the probability of default. We will follow this equilibrium condition for our empirical specification.

3.2 Empirical specification

For each bank and product in our sample, we estimate the following equation with time-varying parameter specification with m breaks (and $m+1$ regimes), which is based on the Bai and Perron (1998, 2003) methodology:

$$\left\{\begin{array}{ll} i_t = \mu_1 + \sum_{j=0}^{J} \rho_{1j} i_{t-j} + \sum_{k=0}^{K} \beta_{1k} \mathrm{MPR}_{t-k} + \sum_{l=0}^{L} \theta_{1l} \mathrm{NPL}_{t-l} + {}_{t} & t = 1, 2, \ldots, T_1 \\ i_t = \mu_2 + \sum_{j=0}^{J} \rho_{2j} i_{t-j} + \sum_{k=0}^{K} \beta_{2k} \mathrm{MPR}_{t-k} + \sum_{l=0}^{L} \theta_{2l} \mathrm{NPL}_{t-l} + {}_{t} & t = T_1 + 1, \ldots, T_2 \\ & \vdots \\ i_t = \mu_t + \sum_{j=0}^{J} \rho_{tj} i_{t-j} + \sum_{k=0}^{K} \beta_{tk} \mathrm{MPR}_{t-k} + \sum_{l=0}^{L} \theta_{tl} \mathrm{NPL}_{t-l} + {}_{t} & t = T_m + 1, \ldots, T \end{array}\right\} \tag{3}$$

where i_t is the lending interest rate at time t, i_{t-j} represents the lagged value of interest rate up to lag J, MPR_{t-k} is the MPR established by the central bank up to lag K and NPL_{t-l} is the share of non-performing loans in each segment up to lag L. Finally, ${}_{t}$ is an error term with mean zero and constant variance.

We depart from the existing literature which was previously used for bank-level data by allowing the possibility of different coefficients over time.

4. Results

4.1 Data

This study utilizes monthly data for Peruvian banks covering the period from September 2010 to August 2022 (144 observations), focusing on lending rates in five categories: corporate, large, medium, small and micro enterprise loans. The data on interest rates and NPLs are obtained from the Superintendencia de Banca y Seguros (SBS). The interest rates are calculated based on daily rates on the last day of each month, capturing the rates offered in the previous 30 days. The interbank rate is used as a proxy for the MPR since it is strongly correlated with the Central Bank's reference rate [4].

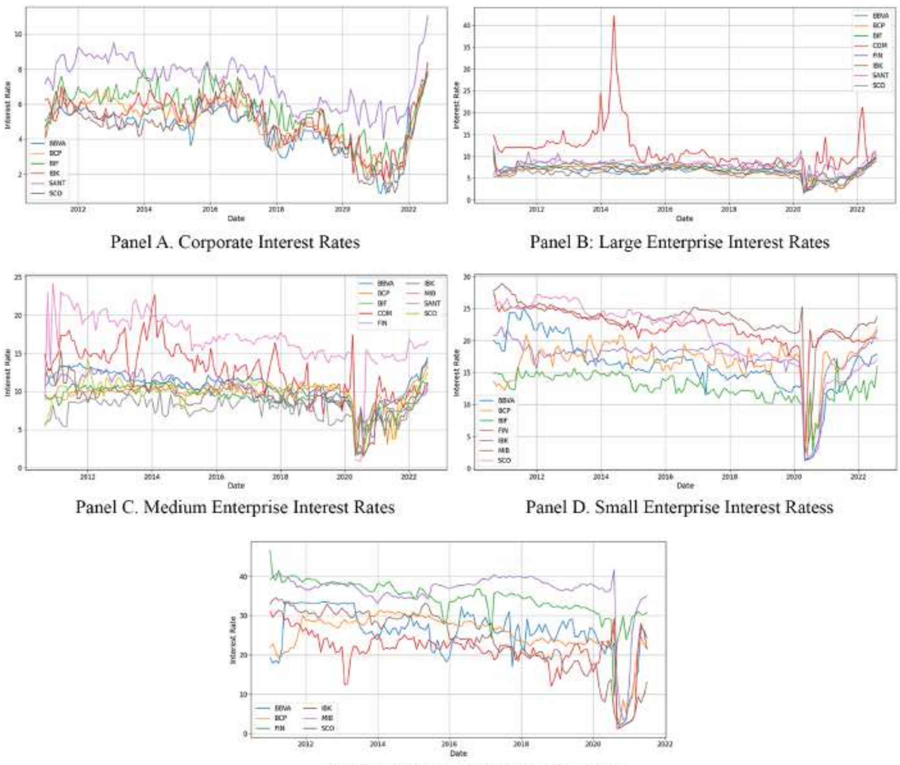
Due to changes in data collection methods after September 2010, earlier data are not directly comparable. Moreover, not all financial institutions reported data consistently across all segments and were excluded. As a result, the sample sizes differed: six banks for corporate loans, eight for large, nine for medium, seven for small and six for microenterprise loans (see Table 1 for details of the institutions).

Interest rate trends over time are shown in Figure 1, which shows the relative stability over time, but with some segment-specific fluctuations. In the corporate segment, rates have displayed a steady decline from 2017, with a trend reversal in late 2021. Lending rates for large enterprises experienced a sharp drop in April 2020 due to COVID-19 related policies, followed by a rebound in late 2021. For medium, small and micro enterprise loans, interest rates have been higher for smaller firms, with notable rate reductions in 2020 because of government initiatives mentioned previously. Figure 2 highlights the close relationship between the Central

Table 1. Bank names and acronyms

Bank name	Acronym	Share of total assets (June 2022)
Banco BBVA Continental	BBVA	19.8%
Banco de Credito del Peru	BCP	35.0%
Banco Interamericano de Finanzas	BIF	3.8%
Banco de Comercio	COM	0.5%
Banco Pichincha	FIN	2.2%
Interbank	IBK	12.9%
Mibanco	MIB	3.3%
Banco Santander	SANT	1.8%
Scotiabank	SCO	15.7%
Excluded banks	–	5.0%

Source(s): Authors' own work



Panel A. Corporate Interest Rates

Panel B: Large Enterprise Interest Rates

Panel C. Medium Enterprise Interest Rates

Panel D. Small Enterprise Interest Ratess

Panel E. Micro Enterprise Interest Rates

Figure 1. Interest rates by segment and financial institution. Source: Authors' own work

Bank's reference rate and the interbank rate, showing key movements such as the reduction from 4.25% to 3.25% between October 2013 and January 2015, another decrease from 4.25% to 2.75% starting in April 2017 and the drastic cut to 0.25% in April 2020 during the pandemic, followed by subsequent increases from mid-2021 onwards to address inflation. These patterns emphasize the importance of macroeconomic policy in shaping banking rates.

4.2 Baseline specification

The results presented here follow the methodology described in Section 3. Separate estimations were conducted for corporate, large, medium, small and micro enterprise loans. For each bank and credit type, the best model specification without structural breaks was determined using ordinary least squares (OLS) from an autoregressive model with up to 12 lags of its own interest rate, the interbank rate and NPL, along with a constant [5]. The Bayesian Information Criterion (BIC) guided the selection of the best model. As a result, not all variables have the same number of lags across specifications.

Once the best specification for each case was identified, the Bai and Perron (1998, 2003) tests for structural breaks were applied. The selection of the final specification follows Bai and Perron (2006). Considering the sample size and the presence of serial correlation, a higher trimming level of 0.25 was used. This ensures that any potential regime identified contains at least 30 observations, to mitigate the bias derived from a small sample.

The inclusion of the NPL variable as a control was informed by previous findings in the literature – particularly for the Peruvian case (Chumpitaz, 2007) – as it tends to reduce the magnitude of the PT coefficients. Banks facing higher default rates have fewer incentives to lower their lending rates after a monetary policy easing because of increased uncertainty about the loan portfolio and pressure on margins. Conversely, if the MPR increases, banks may raise lending rates to compensate for increased risk. The NPL variable is relevant in segments where it differs from zero and exhibits sufficient variance. Thus, it is included in the medium, small and micro enterprise segments, but not in the corporate and large enterprise segments, where the NPL ratio remains close to zero over long periods [6].

4.2.1 Loans for corporate and large enterprises. In the corporate loan segment, the Bai and Perron tests indicate that the effect of the MPR on lending rates changes over time. The number of corporate firms in Peru has not expanded significantly and these borrowers often have alternative funding sources such as foreign banks, parent firms, or capital markets. These factors can lead to higher PT coefficients as banks adjust lending rates in response to policy shifts.

Panel A of Figure 1 shows that the corporate lending rates for the six banks considered exhibit significant variation over time but relatively low variance among banks, suggesting similar timing and number of breaks might be expected across them. Panel A of Table 2 reveals that four out of six banks in the corporate loan segment show structural breaks. Finally, Table 3 shows that those breaks are located mostly between December 2016 and September 2017

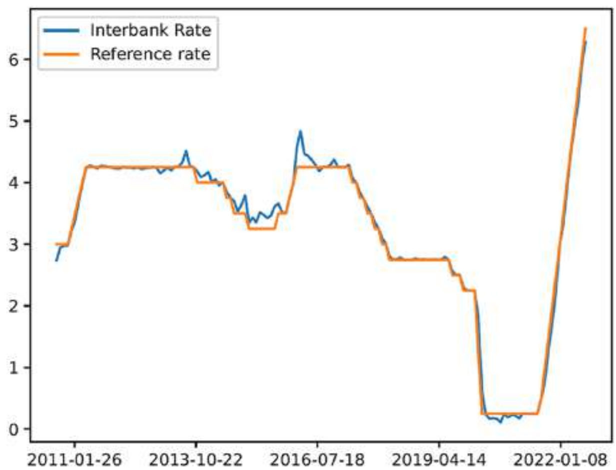


Figure 2. Monetary policy and interbank interest rate. Source: Authors' own work

Table 2. Bai and Perron tests – baseline specification

Panel A

	Corporate							Large						
	BBVA	BCP	BIF	IBK	SANT	SCO	BBVA	BCP	BIF	COM	FIN	IBK	SANT	SCO
UDmax	11.27	23.34 [b]	11.89 [c]	13.64 [c]	12.37	20.34 [b]	31.16 [a]	116.57 [a]	48.28 [a]	62.88 [a]	52.34 [a]	36.69 [a]	19.51 [a]	14.40 [c]
WDmax (1%)	11.27	23.34 [b]	11.89 [a]	13.64	12.37	20.34	31.16 [b]	116.57 [a]	48.28 [a]	62.88 [a]	52.34 [a]	36.69 [a]	19.51 [a]	14.40 [c]
sup $F_T(1)$	11.27	23.34 [b]	11.89 [c]	30.28 [a]	12.29	20.34 [b]	31.16 [a]	116.57 [a]	48.28 [a]	62.88 [a]	52.34 [a]	36.69 [a]	19.51 [a]	14.40 [c]
sup $F_T(2)$	6.63	19.61 [b]	7.27 [b]	17.06 [a]	12.37	16.33 [b]	22.41 [a]	61.24 [a]	31.07 [a]	37.03 [a]	30.49 [a]	23.83 [a]	13.18 [b]	11.47 [c]
sup $F_T(2\|\,1)$	4.00	0	2.88	5.10	17.56	11.27	18.44	17.38	30.13	14.70	18.47	7.97	5.86	8.26
BIC	0	0	0	1	0	0	1	1	1	1	1	1	0	0
LWZ	0	0	0	0	0	0	0	1	0	0	0	0	0	0
Sequential (1%)	0	0	0	1	0	0	1	1	2	1	1	1	1	0
Sequential (5%)	0	1	0	1	0	1	1	1	2	1	1	1	1	0
Sequential (10%)	0	1	1	1	0	1	2	1	2	1	1	1	1	1

Panel B

	Medium									Small						
	BBVA	BCP	BIF	COM	FIN	IBK	MIB	SANT	SCO	BBVA	BCP	BIF	FIN	IBK	MIB	SCO
UDmax	72.12 [a]	52.81 [a]	75.81 [a]	32.01 [a]	23.03 [c]	31.42 [a]	91.11 [a]	25.99 [b]	37.98 [a]	56.64 [a]	50.77 [a]	84.53 [a]	133.27 [a]	109.07 [a]	88.09 [a]	119.98 [a]
WDmax (1%)	72.12 [b]	52.81 [a]	75.81 [a]	32.01 [a]	23.03 [a]	31.42 [a]	91.11 [a]	25.99 [a]	37.98 [a]	56.64 [a]	50.77 [a]	84.53 [a]	133.27 [a]	109.07 [a]	88.09 [a]	119.98 [a]
sup $F_T(1)$	72.13 [a]	52.81 [a]	75.81 [a]	32.01 [a]	23.03 [c]	31.42 [a]	91.11 [a]	25.99 [b]	37.98 [a]	56.64 [a]	50.77 [a]	84.53 [a]	133.27 [a]	109.07 [a]	88.09 [a]	119.98 [a]
sup $F_T(2)$	43.96 [a]	32.16 [a]	42.48 [a]	19.15 [c]	19.13 [c]	19.91 [c]	66.28 [a]	18.81 [c]	29.64 [a]	38.64 [a]	37.90 [a]	64.43 [a]	67.54 [a]	65.80 [a]	42.61 [a]	76.22 [a]
sup $F_T(2\|\,1)$	18.65	56.79 [a]	23.11 [c]	9.08	12.08	11.57	35.27 [a]	10.95	21.50	12.44	30.74 [a]	75.19 [a]	29.50 [b]	26.24 [b]	22.45 [b]	41.22 [a]
BIC	1	1	1	0	0	0	1	0	0	1	0	1	1	1	1	1
LWZ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1

(*continued*)

Table 2. Continued

Panel B

	Medium BBVA	BCP	BIF	COM	FIN	IBK	MIB	SANT	SCO	Small BBVA	BCP	BIF	FIN	IBK	MIB	SCO
Sequential (1%)	1	2	1	1	0	1	2	0	1	1	1	2	1	1	1	2
Sequential (5%)	1	2	1	1	0	1	2	1	1	1	2	2	2	1	2	2
Sequential (10%)	1	2	1	1	1	1	2	1	1	1	2	2	2	2	2	2

Panel C

	Micro BBVA	BCP	FIN	IBK	MIB	SCO
UDmax	31.44 [a]	117.72 [a]	36.54 [a]	15.55	117.56 [a]	28.76 [b]
WDmax (1%)	31.44 [a]	117.72 [a]	36.54 [a]	15.55 [a]	117.56 [a]	28.76 [a]
sup $F_T(1)$	25.86 [b]	117.72 [a]	36.54 [a]	15.55	117.56 [a]	28.76 [b]
sup $F_T(2)$	31.44 [a]	58.25 [a]	35.63 [a]	9.22	57.01 [a]	21.60 [b]
sup $F_T(2\vert 1)$	36.08 [a]	31.55 [a]	91.76 [a]	7.64	27.32 [b]	20.51
BIC	0	1	1	0	1	0
LWZ	0	0	0	0	0	0
Sequential (1%)	0	2	2	0	1	0
Sequential (5%)	2	2	2	0	1	1
Sequential (10%)	2	2	2	0	2	1

Note(s): [a, b, c] denote significance at 1%, 5%, 10%, respectively

Source(s): Authors' own work

Table 3. Baseline specification regression results – corporate loans

	BBVA	BCP	BIF	IBK	SANT	SCO
Regime 1						
Persistence	0.436 [a]	0.703 [a]	0.497 [a]	0.623 [a]	0.870 [a]	0.517 [a]
PT – SR	0.222	0.140	0.342 [c]	0.083	0.064	−0.100
PT – LR	0.394	0.471	0.755 [a]	0.219	0.496 [c]	−0.208
Regime 2						
Persistence	0.175	0.439 [a]	0.337 [a]	−0.146		0.437 [a]
PT – SR	0.564 [a]	0.386 [c]	0.513 [a]	0.817 [a]		0.530 [a]
PT – LR	0.683 [a]	0.688 [c]	0.774 [a]	0.713 [a]		0.943 [a]
T_{B_1}	Aug 2017	Apr 2017	Dec 2016	Sep 2017	None	Mar 2019
95% conf. int.	[Oct 16–Feb 18]	[Oct 16–Sep 17]	[Jun 15–Jan 18]	[Feb 17–Jan 18]		[Jan 19–Jul 19]
$\overline{R}^2$	0.879	0.958	0.850	0.931	0.889	0.899
Log likelihood	−87.157	−22.791	−109.395	−46.477	−79.666	−74.347
Durbin–Watson	1.997	1.982	1.910	2.030	1.955	1.936

Note(s): [a, b, c] denote significance at 1%, 5%, 10%, respectively. T_{B_1} represents the date of the first break
Source(s): Authors' own work

except for Scotiabank in March 2019. Although BBVA shows a break in August 2017 that was not statistically significant, two regimes are assumed for comparability. These changes do not coincide with the COVID-19 pandemic. Instead, they align with MPR reductions starting in April 2017 and late 2019, which triggered a price war in this segment.

According to Table 3, in the second regime, the interbank rate's effect on lending rates becomes statistically significant, while the persistence of the interest rate decreases. The median PT in the short-run (PT-SR) rises from 0.11 in the first regime to 0.52 in the second and the long-run PT (PT-LR) increases from 0.43 to 0.70. Banks with similar break dates exhibit similar PT coefficients in the second regime.

For loans to large enterprises, Panel A of Tables 2 and 4 shows that six out of eight banks have breaks in the last three months of 2019. This might reflect the impact of the Reactiva program. Only one bank had no breaks and Banco de Comercio had a unique break in July 2014. Among the largest banks (see Table 1), PT rates are higher in the second regime, with median short-run PT increasing from 0.14 to 0.39 and long-run PT from 0.34 to 0.80. The results for both corporate and large enterprises partially resemble those found in other emerging markets (Holmes *et al*., 2015; Galindo and Steiner, 2022), where short-term PT is incomplete but approaches unity over the long run, but there are various instances, particularly in the first regime, in which the PT are statistically insignificant.

4.2.2 Loans for medium, small and micro enterprises. For medium enterprise loans, Panel B of Tables 2 and 5 indicates that structural breaks are detected in all but one case, generally around 2016–2018 and late 2019. For small enterprise loans, all banks show at least one break, while for microenterprise loans, two breaks are found in five out of seven banks at the 5% level.

Tables 5–7 illustrate an increase in PT rates after the third quarter of 2019, but the magnitude is inversely related to firm size. However, we always find that the PT-SR is lower than the PT-LR. Prior to 2019, loans to medium firms had a median PT of 0.28 and 0.46 in SR and LR, respectively. In loans to small firms, we find values of 0.50 and 1.20 for both SR and LR-PT. Finally, loans to microenterprises show a PT of 0.54 and 1.56 for SR and LR.

After 2019, higher volatility is reflected in higher PT values. We find a median PT of 0.63 and 1.67 for loans to medium enterprises in both SR and LR, respectively. Those values change to 0.43 and 0.62 in the case of loans to small firms and 0.91 and 1.87 for microenterprises.

Table 4. Baseline specification regression results – large enterprise loans

	BBVA	BCP	BIF	COM	FIN	IBK	SANT	SCO
Regime 1								
Persistence	0.748 [a]	0.840 [a]	0.885 [a]	1.953 [a]	0.050	−0.025	0.202	0.858 [a]
PT – SR	0.065	0.154 [b]	0.268 [b]		0.053	0.588 [a]	−0.430 [c]	0.137 [b]
PT – LR	0.257	0.958 [a]	2.335		0.056	0.574 [a]	−0.538 [b]	0.970 [a]
Regime 2								
Persistence	0.496 [a]	−0.227	0.187	0.687 [a]	1.219 [a]	0.656 [a]	0.539 [a]	
PT – SR	0.387 [a]	1.636 [a]	0.280 [a]		0.120	−0.025	0.376 [a]	
PT – LR	0.810 [a]	1.333 [a]	0.344 [a]		−0.549	−0.072	0.816 [a]	
Regime 3								
Persistence			0.459 [a]			0.425 [b]	0.233	
PT – SR			0.393 [a]			0.604 [a]	0.607 [a]	
PT – LR			0.726 [a]			1.051 [a]	0.792 [a]	
T_{B_1}	Oct 2019	Nov 2019	Dec 2015	Jun 2014	Dec 2019	May 2016	May 2015	None
95% conf. int.	[Nov 18–Jun 20]	[Aug 19–Dec 19]	[Jan 15–May 16]	[Jun 14–Jan 15]	[Mar 19–Dec 19]	[Sep 15–Dec 16]	[Apr 15–Aug 16]	
T_{B_2}			Oct 2019			Oct 2019	Oct 2019	
95% conf. int.			[Mar 19–Jan 20]			[Jul 19–Jan 21]	[Jun 18–Apr 21]	
$\overline{R}^2$	0.916	0.964	0.909	0.842	0.678	0.934	0.881	0.901
Log likelihood	−50.37	−3.99	−58.22	−280.91	−144.24	−49.12	−72.82	−69.41
Durbin–Watson	2.006	2.231	1.882	2.101	2.094	2.065	2.007	1.843

Note(s): [a, b, c] denote significance at 1%, 5%, 10% respectively. T_{B_1} and T_{B_2} represent the date of the first and second break

Source(s): Authors' own work

The above results show notable heterogeneity at the bank level. Among medium enterprises, PT-SR before 2019 was often statistically insignificant for five out of nine banks. PT coefficients tended to be higher in the four largest banks, especially after 2019. A similar pattern emerges for small and microsegments, though some banks had non-significant PT coefficients. In general, the largest banks show higher PT estimates during the COVID-19 period. In microenterprise loans, some coefficients were not statistically significant and the median PT and that of the four largest banks do not significantly differ. Interest rate fluctuations in 2020 may bias results for all segments, justifying the introduction of monthly dummies for that period.

4.3 Baseline specification with COVID-19 dummies

Following Humala (2005), dummy variables for April–December 2020 were introduced after the structural breaks were identified using the Bai and Perron methodology. As corporate and large loans showed no significant interest rate breaks, these segments were excluded from this analysis.

Table 8 shows that adding these dummy variables generally reduces both short-term and long-run PT coefficients. For medium enterprises, most PT-SR values drop below one, except at BCP and Scotiabank, which remain above one. PT-LR estimates exhibit greater heterogeneity, ranging from 0.50 to 5.50, with a median of 0.97. The four largest banks retained higher PT coefficients, with a median PT-SR and PT-LR of 1.02 and 1.57, respectively.

In the small and micro enterprise segments, the introduction of dummy variables leads to substantial variations in PT. The median PT-SR and LR are now 0.22 and 0.43, with three

Table 5. Baseline specification regression results – medium enterprise loans

	BBVA	BCP	BIF	COM	FIN	IBK	MIB	SANT	SCO
Regime 1									
Persistence	0.689 [a]	0.078	0.853 [a]	0.602 [a]	0.325 [b]	0.274 [a]	0.102	−0.256 [c]	0.472 [a]
PT – SR	0.143	0.797 [a]	−0.018	0.767	−0.055	0.604 [a]	−1.371 [c]	1.255 [a]	0.354
PT – LR	0.459	0.864 [a]	−0.122	1.925	−0.081	0.832 [a]	−1.527	0.999 [a]	0.672 [c]
Regime 2									
Persistence	0.635 [a]	0.464	0.696 [a]	5.796 [a]	0.580 [a]	0.323	0.213	−0.146	0.222
PT – SR	0.312 [c]	0.074	0.578	0.395	0.242 [a]	1.133 [a]	0.275	1.115 [a]	1.382 [a]
PT – LR	0.857	0.138	1.903	−0.082	0.577 [a]	1.673 [a]	0.350	0.973 [a]	1.776
Regime 3									
Persistence		0.651 [a]					0.717 [a]		
PT – SR		2.087 [a]					0.626 [a]		
PT – LR		5.986 [c]					2.215 [a]		
NPL	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummies	No	No	No	No	No	No	No	No	No
T_{B_1}	Oct-19	Oct-16	Oct-19	Oct-18	Jul-17	Aug19	Mar-15	Jun-19	Mar-19
95% conf. int.	[Aug 19 – Mar 20]	[Aug 16 – Dec 16]	[Jun 19 – Oct 19]	[Nov 17 – Nov 18]	[May 17 – Jul 18]	[Feb 19 – Dec 19]	[Feb 15 – Jun 15]	[Jan 19 – Sep 19]	[Nov 18 – Apr 19]
T_{B_2}		Aug-19					Mar-18		
95% conf. int.		[Jun 19 – Sep 19]					[Feb 18 – Apr 18]		
$\overline{R}^2$	0.958	0.820	0.910	0.791	0.879	0.914	0.923	0.923	0.835
Log likelihood	−79.59	−132.06	−90.22	−252.19	−139.23	−116.05	−180.72	−180.72	−149.59
Durbin–Watson	1.956	1.589	2.127	1.924	1.810	2.042	2.039	2.039	1.933

Note(s): [a, b, c] denote significance at 1%, 5%, 10% respectively. T_{B_1} and T_{B_2} represent the date of the first and second break
Source(s): Authors' own work

banks showing statistically insignificant parameters. For microenterprises, the median PT-SR and LR coefficients are 0.80 and 2.02, respectively, while the largest banks show a long-term median of 2.42. These results suggest that while the inclusion of dummy variables reduces some biases, it does not reduce the variability in PT across segments, particularly in loans to smaller firms.

For the largest banks, the dummy variables reduce PT coefficients, but they remain larger than those in smaller banks, potentially reflecting more sophisticated analytical capabilities and pricing strategies. Larger PT coefficients following interest rate volatility post-2020 indicate that these banks respond more strongly to changes in funding costs and risk levels.

In the next section, we show using simulations that introducing dummies reduces the bias in the Bai and Perron procedure, particularly when there are large variations in interest rates.

4.4 Simulation study

To address concerns about potential biases in the Bai and Perron procedure, a set of simulation exercises was carried out. The simulations assumed various data generating processes (DGPs) reflecting situations with and without breaks, as well as scenarios including the MPR, NPL, and dummy variables for periods resembling the COVID-19 shock. In particular, the following DGPs are as follows:

(1) DGP1 – AR(1) with no break and MPR as the only explanatory variable: $i_t = \mu + \rho_1 i_{t-1} + \beta_1 MPR_{t-1} + \ \ _t$

Table 6. Baseline specification regression results – small enterprise loans

	BBVA	BCP	BIF	FIN	IBK	MIB	SCO
Regime 1							
Persistence	0.567 [a]	0.025	0.258	0.206	0.643 [a]	0.800 [a]	0.706 [a]
PT – SR	−0.061	4.296 [a]	2.459 [a]	0.037	0.468 [a]	0.377	−0.649
PT – LR	−0.141	4.405 [a]	3.315 [a]	0.047	1.312 [a]	1.889	−2.208
Regime 2							
Persistence	0.590 [a]	0.005	−0.646 [b]	0.772 [a]	0.562 [a]	0.599 [a]	0.663 [a]
PT – SR	0.431 [b]	0.638 [b]	0.288	0.593 [b]	1.161 [a]	0.795 [a]	0.523 [b]
PT – LR	1.053 [b]	0.641 [b]	0.175	2.598 [a]	2.651 [a]	1.984 [a]	1.094 [c]
Regime 3							
Persistence		0.244	−0.202	0.555 [a]		0.472 [a]	0.962 [a]
PT – SR		0.469	1.123 [a]	−0.501		−0.475	−0.430 [b]
PT – LR		0.621	0.934	−1.124		−0.900	0.391 [b]
NPL	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummies	No	No	No	No	No	No	No
T_{B_1}	Apr-17	Aug-15	Nov-15	Apr-15	Nov-19	Feb-15	Aug-15
95% conf. int.	[Mar 17 – Sep 17]	[Jul 15 – Jan 16]	[Oct 15 – Feb 16]	[Mar 15 – Mar 16]	[Oct 19 – Mar 20]	[Aug 14 – Jun 15]	[Jul 15 – Dec 15]
T_{B_2}		Jul-19	Nov-19	Oct-19		Dic-19	Oct-19
95% conf. int.		[May 19 – Oct 19]	[Oct 19 – Jan 20]	[Aug 19 – Nov 19]		[Jun 19 – Jan 20]	[Aug 19 – Dec 19]
$\overline{R}^2$	0.945	0.822	0.855	0.912	0.964	0.846	0.991
Log likelihood	−164.41	−204.25	−158.06	−150.84	−128.26	−209.93	−90.49
Durbin–Watson	2.510	1.796	2.050	2.065	2.005	2.794	2.013

Note(s): [a, b, c] denote significance at 1%, 5%, 10% respectively. T_{B_1} and T_{B_2} represent the date of the first and second break

Source(s): Authors' own work

(2) DGP2 – AR(1) with one break and MPR as explanatory variables: $i_t = \mu + \rho_1 i_{t-1} + \beta_1 MPR_{t-1} + \delta\mathbf{1}(117 \leq T \leq 125) + \varepsilon_t$

(3) DGP3 – AR(1) with one break. MPR, NPL as explanatory variables: $i_t = \mu + \rho_1 i_{t-1} + \beta_1 MPR_{t-1} + \theta_1 NPL_{t-1} + \delta\mathbf{1}(117 \leq T \leq 125) + \varepsilon_t$

(4) DGP4 – AR(1) with one break but with misspecification. The true model is DGP3, but the estimated model is as follows: $i_t = \phi_0 + \phi_1 i_{t-1} + \phi_2 MPR_{t-1} + \delta\mathbf{1}(117 \leq T \leq 125) + \varepsilon_t$

with $\varepsilon_t \sim \mathcal{N}(0, 1)$.

The results show that the tests detect one structural break approximately 6% of the time in DGP1 (with no true break) based on SupF_T, UDMax and WDMax tests, which is close to the expected 5% level [7]. Sequential tests, as well as BIC and LWZ tests, do not identify any breaks in DGP1. For DGP2 to DGP4, which include true breaks, the tests successfully detect at least one break nearly 100% of the time.

However, in all DGPs except DGP1, the detected break is found around period $T = 104$ to 105, about 12 periods earlier than the true break date. In the actual results (Section 5), breaks occur about 6–9 months before the large COVID-19 interest rate reductions. The discrepancy is partly attributed to more complex lag structures in the real data.

We also show that while no bias is found in the first regime, all coefficients present some bias in the second regime after the break. The bias in the constant and the autoregressive

Table 7. Baseline specification regression results – micro enterprise loans

	BBVA	BCP	FIN	IBK	MIB	SCO
Regime 1						
Persistence	0.597 [a]	0.638 [a]	0.833 [a]	0.571 [a]	0.625 [a]	0.972 [a]
PT – SR	0.861	5.604 [a]	−0.652 [c]	0.979 [a]	0.546	0.136
PT – LR	2.139	15.464 [a]	−3.911	2.285 [a]	1.457	4.882
Regime 2						
Persistence	−0.607 [b]	0.917 [a]	0.387		0.571 [a]	0.412 [b]
PT – SR	−0.544	−0.068	0.534		0.715 [a]	0.843 [b]
PT – LR	−0.338	−0.811	0.872		1.667 [a]	1.435 [a]
Regime 3						
Persistence	0.569 [a]	0.059	0.552 [a]		0.251	
PT – SR	0.626	4.486 [a]	−1.548 [b]		3.335 [a]	
PT – LR	1.452	4.766 [a]	−3.459		4.453 [b]	
NPL	Yes	Yes	Yes	Yes	Yes	Yes
Dummies	No	No	No	No	No	No
T_{B_1}	Nov-16	Aug-14	Nov-16	None	Feb-15	Oct-19
95% conf. int.	[Jun 16 – Dec 16]	[Aug 14 – Feb 15]	[Oct 16 – Feb 17]		[Nov 14 – Jun 15]	[Sep 18 – Nov 19]
T_{B_2}	Nov-19	Nov-19	Oct-19		Nov-19	
95% conf. int.	[Nov 19 – May 20]	[Jul 19 – Dec 19]	[May 19 – Nov 19]		[Aug 19 – Dec 19]	
$\overline{R}^2$	0.893	0.943	0.846	0.671	0.938	0.969
Log likelihood	−271.82	−219.28	−266.37	−338.993	−240.92	−236.50
Durbin–Watson	2.065	2.509	1.949	1.858	2.521	2.078

Note(s): [a, b, c] denote significance at 1%, 5%, 10% respectively. T_{B_1} and T_{B_2} represent the date of the first and second break

Source(s): Authors' own work

component of the MPR is notable, though less severe as ρ_1 (the autoregressive coefficient) increases. In DGP4, where the true model includes NPL but the estimated model omits it, biases can exceed 60% for some coefficients.

Introducing dummy variables in the second regime substantially reduces these biases. In DGPs 2 and 3, the bias nearly disappears. In DGP4, bias remains due to omitted variable issues, but is still reduced. Hence, incorporating dummy variables during the period of large rate reductions effectively corrects for bias, particularly in specifications like DGP3 that resemble the empirical model used.

5. Robustness analysis

In this section, we describe various robustness analyses that confirm the results obtained in previous sections. More specifically, those results are related to the estimation by SUR and the introduction of exogenous breakpoints instead of the methodology by Bai and Perron (1998, 2003). Overall, the results are mostly unchanged, signaling the appropriateness of the results obtained in Section 4, [8].

The equations in (3) are estimated separately for each bank using OLS, but it is possible that the error terms across equations are correlated. To address this issue, the baseline model (excluding structural breaks) was re-estimated using SUR. As expected, the estimated coefficients remained similar in magnitude; however, small changes in their statistical

Table 8. Baseline specification with COVID-19 dummies regression results

Panel A

	Medium enterprises								
	BBVA	BCP	BIF	COM	FIN	IBK	MIB	SANT	SCO
Persistence	0.528	0.591 [b]	0.638 [a]	−0.134	0.075	0.445 [c]	0.161 [c]	0.002	0.275 [b]
PT – SR	0.456 [a]	2.247 [a]	0.574 [a]	0.522	0.460 [a]	0.787 [c]	0.471 [a]	0.897 [a]	1.254 [a]
PT – LR	0.967 [b]	5.498 [c]	1.585 [a]	0.460	0.498 [a]	1.418 [a]	0.561 [a]	0.899 [a]	1.731 [a]
NPL	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
T_{B_1}	Oct-19	Aug-19	Oct-19	Oct-18	Jul-17	Aug-19	Mar-18	Jun-19	Mar-19
95% conf. int.	[Aug 19 – Mar 20]	[Jun 19 – Sep 19]	[Jun 19 – Oct 19]	[Nov 17 – Nov 18]	[May 17 – Jul 18]	[Feb 19 – Dec 19]	[Feb 18 – Apr 18]	[Jan 19 – Sep 19]	[Nov 18 – Apr 19]
$\overline{R}^2$	0.992	0.816	0.920	0.836	0.880	0.935	0.986	0.784	0.906
Log likelihood	−6.41	−51.90	−24.50	−66.31	−42.12	−33.64	−17.99	−37.26	−44.24
Durbin–Watson	2.693	1.484	2.205	2.044	1.898	2.489	1.760	2.011	2.088

Panel B

	Small enterprises							Micro enterprises					
	BBVA	BCP	BIF	FIN	IBK	MIB	SCO	BBVA	BCP	FIN	IBK	MIB	SCO
Persistence	0.457 [a]	0.025	−0.334	0.579 [a]	0.497 [a]	0.701 [a]	0.324 [a]	−0.170	0.299 [b]	0.843 [a]	0.710 [a]	0.451 [a]	0.640 [b]
PT – SR	0.379 [b]	4.296 [a]	1.021 [a]	−0.225	0.216	0.094	0.191 [b]	0.763	2.495 [a]	0.234	0.727 [a]	0.943 [a]	0.837 [b]
PT – LR	0.697 [a]	4.405 [a]	0.765 [a]	−0.535	0.429	0.315	0.283 [b]	0.652	3.558 [a]	1.489 [b]	2.508 [a]	1.716 [a]	2.322 [c]
NPL	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
T_{B_1}	Abr-17	Jul-19	Nov-19	Oct-19	Nov-19	Dic-19	Oct-19	Nov-19	Nov-19	Oct-19	None	Nov-19	Oct-19
95% conf. int.	[Mar 17 – Sep 17]	[May 19 – Oct 19]	[Oct 19 – Ene 20]	[Ago 19 – Nov 19]	[Oct 19 – Mar 20]	[Jun 19 – Ene 20]	[Ago 19 – Dic 19]	[Nov 19 – May 20]	[Jul 19 – Dic 19]	[May 19 – Nov 19]		[Ago 19 – Dic 19]	[Set 18 – Nov 19]
$\overline{R}^2$	0.973	0.981	0.852	0.972	0.996	0.998	0.998	0.962	0.943	0.846	0.671	0.938	0.969
Log likelihood	−54.68	−24.19	−43.89	−19.84	−5.14	12.26	13.88	−53.75	−219.28	−266.37	−338.99	−240.93	−236.50
Durbin–Watson	1.597	1.678	2.184	0.883	2.091	2.164	1.835	2.127	2.509	1.949	1.858	2.521	2.078

Note(s): [a, b, c] denote significance at 1%, 5%, 10% respectively. T_{B_1} and T_{B_2} represent the date of the first and second break

Source(s): Authors' own work

significance were observed but only for a minority of banks and segments. Therefore, those variations are not substantial enough to affect the overall conclusions drawn from the independently estimated models.

As a second exercise, we determine an exogenous breakpoint and proceed to estimate the equations via SUR. Given the behavior of interbank and interest rates by segment and bank, February 2020 was selected as the common structural break date for loans to large, medium and microenterprise loans. For the corporate case, we did not select a break because the interest rate series for each bank was visually smooth enough to guarantee the absence of breaks. The main reason for choosing this month lies in the fact that, in the following month (March 2020), a drastic reduction in interest rates took place because of various policy measures implemented by the Peruvian government (see Section 2 of the article).

Therefore, for each segment and financial institution – excluding the corporate segment – two equations were estimated using SUR. These equations included lagged interest rates and lagged NPL as explanatory variables. The first equation corresponds to the period from the beginning of the sample until February 2020, while the second equation covers the period from February 2020 to the end of the sample. The latter includes dummy variables to adjust the baseline model.

The selection of an exogenous breakpoint results in relatively significant changes in the point PT estimates, but about 36% of the PT coefficients were statistically different from those in the baseline model. We found most of the differences in the first regime, but this result is explained because in this case we only defined one breakpoint while the Bai and Perron procedure identified more than one in some cases.

In cases in which the parameters are statistically different from those in the baseline model, the results are not surprising, since the choice of another structural break, even though near the endogenous break obtained by the Bai and Perron methodology, will result in different parameters. Also, the restriction imposed by a common breakpoint when the Bai and Perron procedure determines multiple different breakpoints might explain the obtained results.

As a third exercise, we determined the breakpoint exogenously and then estimated the model using the Bai and Perron methodology. As in the second exercise, the chosen breakpoint was determined in February 2020, except for loans to corporate firms. As a result of this decision, the breakpoints do not exhibit confidence intervals.

Results show that the introduction of an exogenous breakpoint leads us to reject the null hypothesis of equal coefficients from the baseline model in one-third of the PT coefficients. However, it is preferable to determine the breakpoint endogenously, as this approach allows for the identification of additional breakpoints beyond those that can be detected through visual inspection alone.

The fourth and last exercise replaces the interbank rate with the MPR. Results do not change in a substantial way if the same breaks are used: we reject the null hypothesis of equal coefficients in 9% of the PT parameters. In this case, the difference in the coefficients using either of those variables is negligible.

6. Discussion

The findings presented in the Results section highlight that the transmission of the MPR to lending rates in Peruvian banks is neither uniform nor static. The presence of structural breaks at different points in time reveals that changes in the MPR have varying degrees of influence across different loan segments and time periods. While large and corporate customers can access alternative sources of funding, leading to higher and more rapidly adjusting PT coefficients, smaller firms – such as medium, small and micro enterprises – are more susceptible to credit risk factors (NPL) and may not adjust their lending rates as readily following changes in the MPR.

The introduction of the NPL variable is crucial in understanding the dynamics in certain loan segments. Higher default risks imply that banks have fewer incentives to reduce lending rates when the MPR falls due to uncertainty about loan performance and the potential impact on profit margins. Conversely, when the MPR rises, banks may increase their lending rates to offset greater risk. This effect is more pronounced in segments where NPL has sufficient variation. In corporate and large enterprise markets, where the NPL ratio remains near zero, the impact of NPL on PT is negligible.

The timing of structural breaks and changes in PT coefficients often coincides with significant policy shifts and macroeconomic events. For example, the reductions in MPR starting in April 2017 and late 2019 led to price wars in corporate and large enterprise segments, increasing PT in subsequent regimes. Similarly, the COVID-19 period in the first quarter of 2020, marked by unprecedented volatility, affected the identification of breaks.

The use of dummy variables to capture the effects of the COVID-19 period proved essential. Without these dummies, the Bai and Perron procedure would be biased. By introducing dummies after the structural breaks were determined, it was possible to reduce bias and produce more reliable PT estimates. These results, backed by simulation results, underscore the importance of carefully modeling extraordinary events, such as the pandemic's interest rate reductions, to avoid misinterpretation of the underlying PT relationships.

These insights contribute to the broader literature on monetary policy transmission in emerging markets. The complexity observed in the Peruvian case, with imperfect short-term PT but higher long-run PT, especially in larger banks, aligns with previous findings (Holmes *et al*., 2015; Galindo and Steiner, 2022). The results emphasize that PT estimates are sensitive to data availability, model specification, structural breaks and the presence of risk factors. Obtained results are also robust to different estimation methods as well as the determination of exogenous breakpoints or changes in the explanatory variable.

The above results might be explained in various ways. In first place, the funding structure of financial institutions relies on various sources, including deposits, debt or equity. The MPR can affect it, but only if the rate variation is large enough. This is consistent with the higher PT observed during the regime that includes the COVID period, in which the higher volatility in interest rates provided enough incentives for banks to adjust their funding structures.

In second place, the composition of the loan portfolio also plays an important role. Within each client segment, there are different types of products and maturities, which are funded differently. In this work, each segment has been considered as a whole, without accounting for these internal differences. For example, a short-term loan may be more sensitive to the reference rate, while a medium- or long-term loan may be more influenced by another one. This may lead to different – or even insignificant – effects across cases due to aggregation bias. This remains an open question for future research.

Third, not all financial institutions have the same ability to adjust prices in response to changes in their cost components (Phillips, 2018). Depending on their level of technological development and internal governance schemes, price adjustments may be imperfect. Finally, there is the issue of market structure. There is substantial evidence indicating that in more concentrated markets or in those with fewer financing options, prices tend to be more rigid. As mentioned in Section 1, the credit market in Peru is among the most concentrated in the region. This could explain the observed rate rigidity and the relatively low degree of PT in some segments. In conclusion, incorporating control variables like NPL, allowing for structural breaks and introducing dummy variables for exceptional periods significantly improves the accuracy and interpretability of PT estimates. The results presented and discussed here provide a more detailed understanding of how monetary policy interacts with the banking sector in an emerging market context, reinforcing the importance of models that can adapt to changes in economic conditions and data generation processes.

7. Conclusions

This paper examines the relationship between the MPR and bank loan interest rates in Peru from September 2010 to August 2022, focusing on loans to different firm sizes. Results indicate significant heterogeneity across banks and time, particularly noting regime changes linked to Central Bank's rate fluctuations. Generally, low or statistically insignificant PT coefficients in both short (PT-SR) and long run (PT-LR) are observed when the reference rate is stable. However, significant rate changes, like those during the COVID-19 pandemic, lead to statistically significant PT coefficients.

Post-third quarter of 2019, PT rates for corporate, large and medium firms align, with median PT-SR at 0.55 and PT-LR at 0.87. For small and micro enterprises, PT rates differ; the first segment shows reduced PT rates (0.22 and 0.43), while the second segment increases significantly (0.80 and 2.02). Robustness checks validate these findings, with larger banks showing higher rate responses, especially after the 2020 period.

Key factors influencing PT variability include the degree of interest rate fluctuations: substantial changes increase PT, which is particularly evident as major banks exhibit higher PT during rate hikes. In the small and micro enterprise sectors, larger PTs are consistent across all regimes, influenced by competitive pressures from additional market players like Cajas Municipales, Cajas Rurales and informal lenders, as well as higher risk levels.

This study's focus is limited to loans to firms and future research could explore PT effects across various loan maturities, including different types of financial institutions and expand to consumer loans, credit cards and mortgages.

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Notes

1. For an extensive literature review for the Euro area, see Andries and Billon (2016) and Bennouna (2019) for developed countries.
2. In the case of lending rates, the author analyzes only short term (less than 360 days) and long term (more than 360 days) rates.
3. FAE stands Fondo de Apoyo Empresarial a Micro y Pequeñas Empresas, or Business Support Fund for Micro and Small Enterprises, as per its Spanish acronym.
4. During the study period, the correlation between the Monetary Policy Rate (MPR) and the interbank rate was 0.985. To assess the robustness of our findings, we conducted an additional analysis in which the interbank rate was replaced by the MPR. The results, presented in the supplementary material, indicate that the choice of rate does not materially affect the conclusions shown in this article.
5. The base specification was also tested for autocorrelation even after the inclusion of the lagged variables. Even though we find evidence of autocorrelation for higher order lags, particularly in the small and micro enterprise segments, we choose not to correct the standard errors since it might affect the power and size of the Bai and Perron tests. The results are shown in the supplementary material.
6. Robustness tests were conducted by excluding the NPL variable. Results are shown in the supplementary material.
7. Simulation results are reported in the supplementary material.
8. Detailed results for each of the analysis detailed in this section are in the supplementary material.

Supplementary material
The supplementary material for this article can be found online.

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Further reading

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