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Bank's Non Performing Loans in Latin America

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Abstract

This paper seeks to explore developments in the Latin American financial system over the last decade by analyzing the factors that determined non-performing loans during 2015-2024 and, above all, by showing that banks responded differently depending on internal and external factors. We explore financial and macroeconomic variables for Brazil, Colombia, Chile, Mexico, and Peru. Specifically, when we split the sample, the results are heterogeneous, with some variables affecting non-performing loans more than others. The split is based on the pandemic, which led to structural changes in the performance of the financial system in emerging countries.

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1. Introduction

Banking efficiency is a critical component of any financial institution. It may be related to the institution's balance sheet and cash flow, credit allocation, financial inclusion, and economic growth. In Latin America, a region characterized by structural inequality, volatile macroeconomic conditions, and financial sector reforms, banking efficiency has received growing academic and policy attention.

This paper explores the state of banking efficiency in Latin America and how it is linked to non-performing loans (NPLs).[1] Banking efficiency generally refers to a financial institution's ability to use resources (inputs) to generate maximum outputs, such as loans and financial services. It can be approached from the perspectives of cost and profit efficiency (Charnes et al., 1978).

Efficiency can also reflect non-financial factors, including innovation, technology adoption, and managerial effectiveness. In emerging economies, for example, those in Latin America, it is also related to financial stability and inclusion (Inter-American Development Bank, 2022; Moody's Investor Services, 2023).[2]

Banking efficiency in Latin America varies. Countries such as Chile, Mexico, and Colombia have relatively modern and stable banking systems, while others still struggle with inefficiencies due to overregulation, poor governance, and political instability and macroeconomic volatility (World Bank, 2023).

According to studies by the Inter-American Development Bank (2022), Latin American banks tend to be less efficient than their counterparts in advanced economies. Operational costs may be higher, and profit margins are often overstated due to limited competition rather than bank productivity.

Despite this, return on assets (ROA) and return on equity (ROE) in the region remain strong, suggesting that profitability is driven more by wide credit spreads than by genuine efficiency. There is considerable scholarly activity on NPLs in Latin America.

Ozil (2019)[3] concludes that greater financial intermediation and foreign bank presence are positively associated with NPLs, indicating that expanded lending activity and foreign participation may increase credit risk. Surprisingly, higher banking efficiency (CE) is also linked to higher NPLs, while higher loan loss coverage (LLC), banking system stability (Z-score), and competitiveness (Lerner Index) are associated with lower NPLs. Banking efficiency is not associated with competitiveness; it is neither a sufficient nor a necessary condition.

In the context of analyzing the determinants of NPLs, Katsampoxakis and Basdekis (2022) identify the macroeconomic and banking determinants influencing NPLs across ten European countries (Greece, Italy, Portugal, Belgium, Germany, Spain, France, Ukraine, Switzerland, and Austria). The authors show that macroeconomic variables are relevant in explaining NPLs. Ho-

[1] A study by Guillen (2025) explores the determinants of non-performing loans in Peru.

[2] Additional sources include Banco Central do Brasil (2022), CNBV (Comisión Nacional Bancaria y de Valores) (2023) and INEGI (Instituto Nacional de Estadística y Geografía) (2023)

[3] Datasets from different countries, not only Latin America, are used.

wever, banks' capital adequacy ratios do not show significant effects.[4] For an emerging country such as Nigeria, Eke et al. (2020) find that macroeconomic risks significantly influence both bank credit behavior and NPL incidence.

On the other hand, reversing the direction of causality, Fernández (2020) concludes that increases in NPLs and decreases in financial stability significantly intensify banking competition, particularly among non-listed banks. In addition, banking competition is not associated with efficiency but rather with the sector's competitiveness.

Delinquency is one of the main factors explaining financial crises. An institution that begins to experience a deterioration in its credit portfolio sees its profitability harmed by an increase in the proportion of loans with unpaid interest, in addition to disruptions in cash flow. The profitability problem worsens given that the regulated entity must increase its provisions for delinquent loans, which immediately affects reported profits. Thus, a significant increase in delinquency causes the default problem to become one of profitability and liquidity, and ultimately a solvency problem if the institution begins to generate losses and provisioning shortfalls.

NPLs' importance as a factor underlying banking crises has been observed in several episodes of financial collapse. Friedman and Schwartz (1963) point out that, in the U.S. banking crisis of the 1930s, the percentage of bad loans was lower in the early 1920s than in the late 1920s, suggesting that while bank runs (liquidity crises) caused the greatest number of bankruptcies, the deterioration in asset quality triggered the crisis by undermining confidence in the banking system. This relationship is also documented by White (1984), who indicates that the poor performance of banking assets was an important factor increasing the probability of banking company bankruptcy in the 1930s. In contrast, Beattie et al. (1995) provide a series of examples of financial institution bankruptcies in which significant deterioration in credit portfolios was observed in the periods preceding bankruptcy.

The deterioration of asset quality affects bank solvency and, therefore, the stability of financial systems, as pointed out by Caprio and Klingebiel (1996), who emphasize that this deterioration dilutes bank capital, increasing the likelihood of banking crises. In contrast, Mishkin (1997) identifies a second mechanism by which the deterioration of the loan portfolio increases financial instability through its adverse effect on asymmetric information problems, generating panic and explaining contagion effects. He shows how, in the Mexican crisis of 1995, the increase in problem loans played an important role in the early stages of the crisis (Mishkin, 1997). For an increase in the NPL portfolio to trigger a financial crisis, it must be widespread across many financial institutions and sufficiently severe, prolonged, and unexpected.

We focus on the determinants of delinquency in a selected set of Latin American countries. This paper is relevant for policy analysis within the region aimed at preventing financial crises, such as the 2009 subprime crisis, as well as other crises experienced worldwide.

[4] Along this line of research, Makri et al. (2014) find, in a similar study in Europe, that the NPL ratio can be explained by bank-specific indicators such as capital adequacy ratio, the loans-to-deposits ratio, ROA, ROE, and lagged NPLs, as well as by macroeconomic factors.

2. The Non-Performing Loan (NPL) Situation in Latin America

Generally, the increases in delinquency discussed above have occurred after supply shocks that affected sectors or regions where banks were highly concentrated, as in the case of the bankruptcy of state-owned banks in the United States. However, in the case of multi-sector banks operating nationwide and diversifying across economic sectors, what has generally been observed is that crises are preceded by a credit boom, as occurred in the 1930s in the United States and in the crises in Spain, Mexico, Argentina, Singapore, and other emerging countries.

The traditional mechanism involves an exceptional increase in credit supported by a significant improvement in economic activity and widespread over-optimism and myopic behavior, which obscures the speculative nature of the credit boom as it begins to develop. Thus, a mismatch arises between the economic cycle and the credit cycle, with the latter ending after the former, thereby deepening the decline in economic activity. At this point, as credit continues to grow while output enters a downturn, credit risk increases and firms become over-indebted, triggering higher interest rates and delinquencies.

In the case of Latin America, loans are linked to GDP growth. As shown in the figures below, in general, these variables have a positive relationship. A problem arises when a boom is followed by a major recession that may trigger a decline in loans and, consequently, a financial crisis. GDP performance before and after the pandemic differs across countries; however, overall, when it improves, banks tend to extend more credit because there is an opportunity to earn profits with a low probability of borrower default.

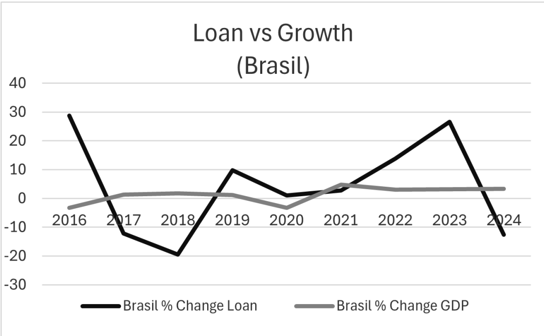
Brazil experienced a drop in GDP before the pandemic, and this variable then recovered[5] alongside an increase in loans. Chile showed the same relationship, but with a different pattern in GDP growth. Colombia did not experience a severe recession in 2020, but loans are also linked to the behavior of the country's total output.

Finally, in the cases of Peru and Mexico, the evolution of GDP is very similar, as is the annual variation in loans. The pandemic hit these countries significantly due to informality[6] (Loayza, 2020).

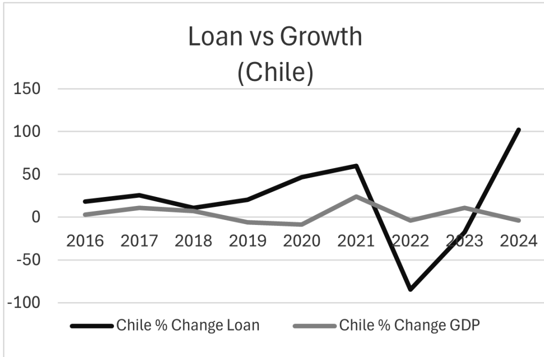
[5]Brazil is a BRIC country, along with Russia, India, and China. The inclusion of the latter is based on their strong performance in certain macroeconomic variables.

[6]Informality makes it impossible to successfully implement subsidies and keep people at home. People need to work. "Die of starvation or of COVID."

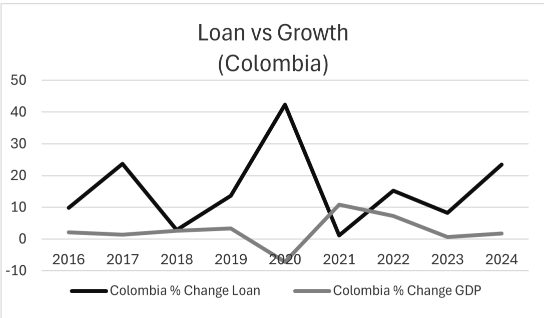
Figure 1. Loan Growth vs. GDP Growth by Country



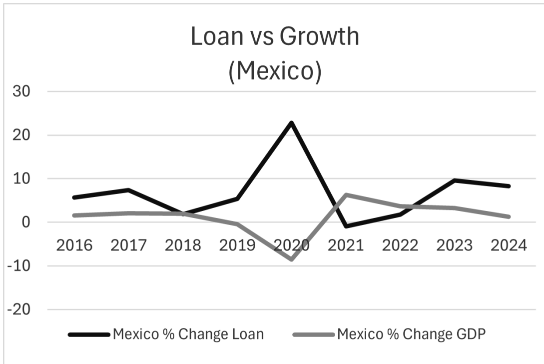
(a) Brazil



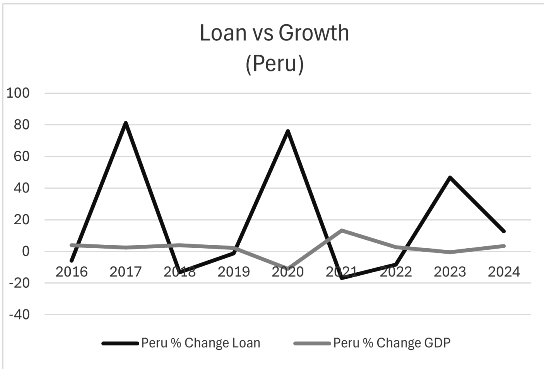
(b) Chile



(c) Colombia



(d) Mexico



(e) Peru

Note: Since the data span the period from 2015 to 2024, the growth rate is measured on an annual basis.

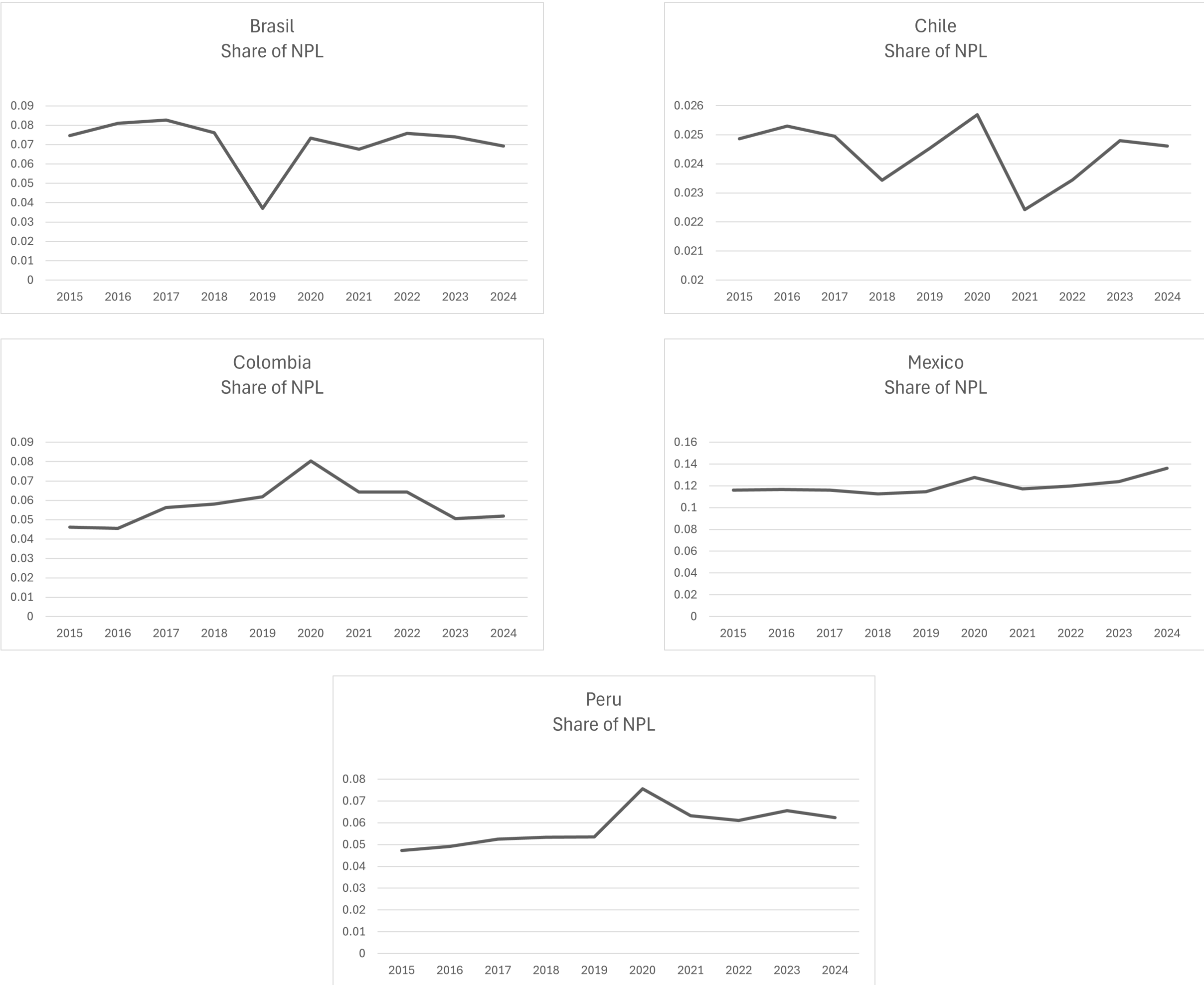
Below, we report data on NPL ratios.[7] Typically, an increase in the overdue portfolio leads banks to significantly reduce loan growth. The results are relatively homogeneous for delinquency, except in the case of Chile, where the delinquency ratio was below 3 %. The rest of the sample

[7] The delinquency ratio is defined as delinquent loans as a share of total loans. It represents the period and country average, respectively.

reached delinquency ratios of 6–7 %. The 2020 pandemic marked a structural shift that disrupted the relationship between loans, delinquency, and GDP growth. The recession was severe and varied with the degree of informality[8] (Loayza, 2020). This situation brings about several changes in the financial variables under assessment. The figures illustrate a peak in delinquency rates in 2020.

[8]Informality led to heterogeneous outcomes from both an economic and health-related perspective. The contrast between emerging and developed countries is clear. Our data correspond to emerging markets, but there is still a certain degree of heterogeneity.

Figure 2. Loan Growth vs. GDP Growth by Country



3. Methodology and Model Specification

We test the hypothesis on the determinants of delinquency using a panel dataset with 250 observations, including financial and macroeconomic variables for the top five banks in the following countries: Brazil, Colombia, Chile, Mexico, and Peru. We selected the most significant banks, which account for 70 % of each country's deposits. Given the high degree of banking concentration in emerging economies, the aim is to prevent financial instability resulting from their political and financial vulnerabilities (Drake, 1989).[9]

The analysis of the factors affecting credit quality has not been examined exhaustively in the literature. This gap is also common in research on banking in emerging markets. Most research

[9] Edwin W. Kemmerer was an American economist who advised several Latin American countries, promoting plans to reform the financial system, as well as fiscal and monetary policies. He advised in the Philippines (1904), Mexico (1917), Guatemala (1919), Colombia (1923), Chile (1925), Ecuador (1926), and Peru (1931). He recommended banking concentration to reduce vulnerability under capital flight scenarios. Policies similar to Kemmerer's were implemented in Latin American countries but did not visit. For this reason, banking in emerging economies is regulated under the Basel framework, whereas advanced economies have their own, more flexible regulatory regimes.

has focused on understanding individual loan delinquency through borrower characteristics or historical default data, leading to credit scoring and credit risk models (Altman and Saunders, 1996). However, it is also valid to consider that delinquency depends not only on the bank's credit portfolio management but also on external factors linked to the economy. We considered large banks, which may be subject to certain influence from internal and external factors, unlike smaller banks, which do not have the economies of scale needed to withstand vulnerabilities.

Our paper is relevant because large banks have a significant impact on key macroeconomic variables. This is known as the "too big to fail" phenomenon in the banking literature (Ennis and Malek, 2005). We analyze these determinants using internal and external factors. For the external factors, we consider GDP growth and the central bank's interest rate. According to the previous section, the former affects credit supply, as well as credit quality and borrower default probability. The latter affects bank liquidity and the probability of debt repayment.[10] In addition, regarding the recent Silicon Valley crisis, there is a discussion as to whether the main factor triggering these bank failures was an external shock (linked to increases in the FED interest rate) or the management of financial assets (Dinh, 2023). Emerging markets are subject to portfolio dollarization, which explains banks' exposure to capital flight that affects the currency and debts in dollars (Calvo and Vegh, 1999).

There are also internal factors that depend largely on the bank in emerging markets. Exposure to political instability and capital flight is not relevant in this case. The company's internal or specific factors have rarely been addressed in the literature, except for studies by Keeton and Morris (1987), Sinkey and Greenawalt (1988),[11] and Berger and Mester (1997). According to Keeton and Morris (1987), although most of the variations in delinquency can be explained by local economic conditions, the risk-taking behavior of banks is an important factor. Similarly, Sinkey and Greenawalt (1988) find that the average return on loans, dependence on wholesale funds, and loan-to-asset ratio have a positive and significant relationship with delinquency.

Conversely, in Berger and Mester (1997), the problem of operational inefficiency is a sign of poor management and, consequently, of poor credit selection. However, the authors point out that although there was a positive relationship between operating costs and delinquency in the group of banks analyzed, indicating poor management, in some cases, the ratio was negative, which could reflect an efficient increase in operating expenses (better staff quality, better systems, among others). Finally, the authors analyze the moral hazard through banks' capital levels, noting that the most leveraged banks translate increases in leveraging into higher delinquency, suggesting that they have the greatest incentives to take risks.[12]

Therefore, for internal factors, we distinguish two categories. First, internal determinants associated with a bank's risk-taking behavior are measured by the bank's leverage level and market share. Increases in leverage or in the share of loans in the system are expected to reflect more aggressive risk-taking behavior, implying a greater willingness to take on bad loans. We

[10] For the discussion of external factors, see Pigou (1928) and Mishkin (1997).

[11] See Beattie et al. (1995).

[12] The same idea is found in Marsh and Paul (1996) and Guillen (2025). The latter estimates and evaluates efficiency in the recent Silicon Valley Bank case.

use loans as a percentage of capital[13] and banking concentration to capture this effect.[14]

Second, internal factors associated with productive efficiency will be measured with Data Envelopment Analysis (DEA).[15] As Berger and Mester (1997) highlight, the relationship between productive expenses (inefficiency) and delinquency could be positive, indicating poor management, or negative, suggesting efficiently allocated expenses. In addition, the DEA variable is also used as a predictor of bank failure (Guillen, 2025) in the CAMEL models (Capital, Assets, Management, Earnings, and Liquidity). The dependent variable is the non-performing loans of each bank, which is measured as a share of assets.[16]

Additionally, a delinquency lag was included to measure the influence of past information on current delinquency and to control for the autoregressive effect in the model. Delinquency is expressed as a percentage of assets. The external factors expected to affect delinquency negatively and positively are, respectively, GDP growth and the interest rate.[17] Thus, the model specification for NPL determinants, including internal and external factors, can be expressed as follows:

$$
\begin{aligned}
NPL_{it} = \alpha &+ \beta_1 NPL_{i,t-1} + \beta_2 Leverage_{it} + \beta_3 DEA_{it} \\
&+ \beta_4 DEAR_{it} + \beta_5 MarketShare_{it} + \beta_6 MarketShareR_{it} \\
&+ \beta_7 GDPGrowth_t + \beta_8 CentralBankInterestRate_t + \ldots
\end{aligned}
\tag{1}
$$

Where:

- NPL_{it}: non-performing loan (NPL) ratio as a percentage of total loans outstanding
- $NPL_{i,t-1}$: lagged non-performing loans ratio
- $Leverage_{it}$: loans-to-capital ratio for bank i in period t
- DEA_{it}: absolute banking efficiency, compared across all countries[18]
- $DEAR_{it}$: banking efficiency relative to country
- $MarketShare_{it}$: deposit ratio for sample countries[19]
- $MarketShareR_{it}$: deposit ratio relative to country
- $GDPGrowth_{it}$: country GDP growth in period t
- $CentralBankInterestRate_{it}$: country's interest rate in period t

[13] This variable indicates bank leverage and the risk assumed by the bank.

[14] Concentration is measured relative to the country and the overall sample. It also serves as an indicator of market power that may influence the delinquency outcomes.

[15] See the seminal paper by Charnes et al. (1978), which has been applied to different samples worldwide. The next section explains how this indicator is constructed for each bank.

[16] We use ratios to avoid heteroscedasticity problems in the panel estimation.

[17] An increase in the interest rate is equivalent to withdrawing liquidity, and NPLs may rise.

[18] The estimation is performed both within each country (relative) and with respect to the full sample (absolute).

[19] Estimated across the full set of countries, it is the ratio of loans to the total, computed either for the full sample or for each country.

3.1 Efficiency Estimation

Efficiency is an indicator that captures the management of inputs and outputs by the bank under assessment. There are two types of efficiency estimation. The first uses a stochastic method that is very similar to a regression framework, where residuals reflect efficiency. The second is a non-parametric technique that captures the efficient allocation of inputs to produce outputs. The latter is the DEA approach, developed by Charnes et al. (1978).

The DEA is based on the seminal work by Charnes et al. (1978). The latter introduced the basic idea of measuring relative efficiency using Euclidean distances from a given observation to an optimal "relative frontier." The term "relative" is used because efficiency is estimated with respect to a selected sample. The bank located on the frontier receives a score of one, whereas banks located below the frontier receive scores lower than one. Charnes et al. (1978) used a linear programming approach to estimate efficiency measures using multiple inputs and outputs simultaneously.[20]

The linear program employed by Charnes et al. (1978) calculates the efficiency scores given by

$$\begin{aligned} &\text{mín } \phi \\ \sum \lambda_j x_{ij} + S_i^+ &= \phi x_{ij_0} \\ \sum \lambda_j y_{rj} - S_r^- &= y_{rj} \\ S_i^+, S_i^- &\geq 0 \\ \lambda_j &\geq 0 \\ &\forall i, j, r \end{aligned} \tag{2}$$

Where x_{ij} is the amount of ith input at PPF j, y_{rj} stands for the amount of rth output from PPF j, and finally j_0 is the PPF to assess. S_i^+, S_r^- are the slack variables.[21]

The linear program is called the input-oriented model[22] with variable returns to scale (VRS).[23] The first restriction says that a PPF j_0 cannot use more resources than any other PPF or a linear combination of PPFs. The second restriction means that no other PPF or combination of PPFs has at least the same amount of output as PPF j_0. At the minimum $\phi = 1$ and $S_i^+ = S_r^- = 0$ for all i and r. If, at the minimum, the slack variables are non-zero, the solution is weakly efficient. Our estimation resulted in fully efficient, which means that the slack variables (S_i^+, S_r^-) are zero at the minimum.

For inputs, we use fixed assets, deposits, interest expenses, and non-interest expenses. The outputs are interest income and non-interest income. The criteria for the selection of inputs and

[20] This is a useful way to measure efficiency, since ratios such as personnel or personnel expenses as a share of assets do not necessarily replicate the input-output approach proposed by Charnes et al. (1978).

[21] See Charnes et al. (1978) for a detailed explanation.

[22] There is another approach besides the input-oriented model, which is called the output-oriented model. The maximization of outputs is the dual of the linear program introduced by Charnes et al. (1978).

[23] There are models that include constant returns to scale (CRS) instead of VRS. VRS signifies that in a production process, the operations will follow increasing or decreasing returns to scale. Note also that some firms that have not been efficient in the models so far may become efficient if we allow a variable returns to scale assumption (relaxing the CRS assumption).

outputs are consistent with the scope of most of the banking literature.[24] The general idea is that banking intermediation uses deposits as an input to provide loans.

The period ranges from 2016 to 2024, covering both the pre- and post-pandemic periods. The pandemic hit emerging markets severely, both in terms of health and the economy. Countries, for example, Peru experienced the largest recession in the region. In the second quarter of 2020 (Loayza, 2020), Peru's GDP dropped by one third, causing a significant rise in unemployment. This also had a negative effect on banks' balance sheets. Therefore, the period under consideration is particularly interesting to analyze, as it captures the years before and after a unique episode. Table 1 presents descriptive statistics for the financial variables in our database, and Table 2 illustrates statistics for the efficiency estimates for each bank.[25]

Table 1

Summary Statistics for the Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
NPL ratio	250	0.242103	2.767615	0.0003221	43.80677
Loan ratio	250	0.5909804	0.1771775	0.0007107	0.8810775
Absolute DEA	250	0.9685888	0.0621798	0.5929	1
Relative DEA	250	0.9745012	0.0527159	0.7672	1
Absolute concentration	250	0.1624192	0.0974812	0.0357332	0.6408963
Relative concentration	250	0.2	0.0781918	0.0294672	0.4284905
GDP growth	250	0.0197781	0.0588483	-0.1086964	0.2383816
Leverage	235	6.85536	3.782035	0.0093382	25.6339
Reference rate	250	0.4246795	1.67983	-0.8888889	9

Source: Central banks of each country
Preparation: Authors' own elaboration

[24]See Berger and Mester (2003), Barr et al. (1999), and DeYoung (1998).
[25]The estimation procedure was described in the previous section.

Table 2a
Relative Efficiency Scores

Country	Year	Min	Q1	Median	Mean	Q3	Max
Brazil	2015	0.9317	1	1	0.9863	1	1
Brazil	2016	1	1	1	1	1	1
Brazil	2017	1	1	1	1	1	1
Brazil	2018	0.9372	0.9385	1	0.9751	1	1
Brazil	2019	1	1	1	1	1	1
Brazil	2020	0.77	0.8817	0.9514	0.9206	1	1
Brazil	2021	0.9601	1	1	0.9920	1	1
Brazil	2022	0.8811	0.9581	1	0.9678	1	1
Brazil	2023	0.8468	0.9748	0.9924	0.9628	1	1
Brazil	2024	0.8222	0.9442	0.9656	0.9464	1	1
Chile	2015	0.7962	0.9999	1	0.9592	1	1
Chile	2016	0.7767	1	1	0.9553	1	1
Chile	2017	0.7672	1	1	0.9534	1	1
Chile	2018	0.8360	1	1	0.9672	1	1
Chile	2019	0.9297	1	1	0.9859	1	1
Chile	2020	0.8381	1	1	0.9676	1	1
Chile	2021	0.9616	1	1	0.9923	1	1
Chile	2022	1	1	1	1	1	1
Chile	2023	0.9124	1	1	0.9825	1	1
Chile	2024	0.8775	1	1	0.9755	1	1
Colombia	2015	0.8810	0.9265	1	0.9615	1	1
Colombia	2016	0.9447	1	1	0.9889	1	1
Colombia	2017	0.9884	1	1	0.9977	1	1
Colombia	2018	0.8574	1	1	0.9715	1	1
Colombia	2019	0.9599	1	1	0.9920	1	1
Colombia	2020	0.9452	1	1	0.9890	1	1
Colombia	2021	0.9523	1	1	0.9905	1	1
Colombia	2022	0.9220	1	1	0.9844	1	1
Colombia	2023	0.9546	1	1	0.9909	1	1
Colombia	2024	0.9730	1	1	0.9946	1	1
Mexico	2015	0.8618	0.8899	1	0.9503	1	1
Mexico	2016	0.8404	0.8910	1	0.9463	1	1
Mexico	2017	0.7848	0.8909	1	0.9351	1	1
Mexico	2018	0.8278	0.9302	1	0.9516	1	1
Mexico	2019	0.8314	0.9483	1	0.9559	1	1
Mexico	2020	0.8616	0.9932	1	0.9710	1	1

Preparation: Authors' own elaboration

Table 2a
Relative Efficiency Scores (continued)

Country	Year	Min	Q1	Median	Mean	Q3	Max
Mexico	2021	0.9263	1	1	0.9853	1	1
Mexico	2022	0.9919	1	1	0.9984	1	1
Mexico	2023	0.9977	1	1	0.9995	1	1
Mexico	2024	0.8534	1	1	0.9707	1	1
Peru	2015	0.9027	0.9288	0.9653	0.9594	1	1
Peru	2016	0.9320	0.9342	1	0.9732	1	1
Peru	2017	0.8494	0.9440	1	0.9587	1	1
Peru	2018	0.9361	0.9938	1	0.9860	1	1
Peru	2019	0.9179	1	1	0.9836	1	1
Peru	2020	0.8615	1	1	0.9723	1	1
Peru	2021	0.7866	0.8721	1	0.9317	1	1
Peru	2022	0.8685	0.9973	1	0.9732	1	1
Peru	2023	0.9212	1	1	0.9842	1	1
Peru	2024	0.9502	1	1	0.9900	1	1

Preparation: Authors' own elaboration

Table 2b
Absolute Efficiency Scores

Year	Min	Q1	Median	Mean	Q3	Max
2015	0.5929	0.9536	1	0.9552	1	1
2016	0.8107	0.9987	1	0.9769	1	1
2017	0.8351	1	1	0.9811	1	1
2018	0.8089	0.9985	1	0.9789	1	1
2019	0.7942	1	1	0.9856	1	1
2020	0.7484	0.9329	1	0.9557	1	1
2021	0.7512	0.9378	1	0.9606	1	1
2022	0.6950	0.9958	1	0.9664	1	1
2023	0.8282	0.9938	1	0.9650	1	1
2024	0.8202	0.9337	1	0.9606	1	1

Preparation: Authors' own elaboration

Table 2a reports relative efficiency measurement using the DEA estimation explained in the previous section. This measure is relative because efficiency is estimated for each period and country. The estimator is always relative to the selected set of competitors, in our case, banks within the same country. By contrast, Table 2b reports efficiency estimators for the full sample of countries and for each period between 2015 and 2024. The latter is an absolute measure, since a bank that is efficient within a given country does not necessarily achieve the same score under the absolute measure. A bank's relative market power may influence the results.

3.2 Model Estimation

The results of the model specification explained in Section 3 are presented below. Tables 3a, 3b and 3c provide the model results for different time periods ranging from 2015 to 2024, 2015 to 2019, and 2020 to 2024. These periods correspond to the full sample, which we split into two parts considering a significant episode that may have induced structural changes in the financial variables: the 2020 pandemic. The first table includes an assessment of the full dataset, the second covers the period preceding the pandemic, and the third considers post-pandemic effects. We estimated with Arellano Bond which is the best estimator for this data sample.

Although the initial Hausman test suggested the appropriateness of a Random Effects (RE), this test is strictly designed for static models and is inconsistent in a dynamic panel data context. In models including a lagged dependent variable (NPL_{t-1} lagged), the RE assumption of zero correlation between the individual effect and the regressors is violated by construction, as NPL_{t-1} is inherently correlated with the time-invariant error component. To address this endogeneity and the potential Nickell bias (given our small T), we employed the Difference GMM estimator (Arellano-Bond). The model's validity is confirmed by the Hansen test fails to reject the null hypothesis of instrument exogeneity. Furthermore, the Arellano-Bond test for AR(2) shows no evidence of second-order serial correlation, validating the use of lagged variables as instruments. Finally, by using the collapse option, we maintained a parsimonious instrument count (8 instruments for 26 groups), preventing the "instrument proliferation" bias common in GMM estimations (See Table 3d).

Table 3a

Determinants of Non-Performing Loans (2015–2024)

	Arellano Bond Estimation		
	(1)	(2)	(3)
	Model 1	Model 2	Model 3
	NPL Ratio	NPL Ratio	NPL Ratio
NPL Lagged	-0.0170	-0.0163	-0.0290
	(-0.0164)	(-0.0157)	(-0.0280)
DEAR	0.0561***		0.0704***
	(0.0319)		(0.0400)
Market ShareR	0.0965		0.184
	(0.0870)		(0.165)
Leverage	-0.00656	-0.00565	-0.0106
	(-0.257)	(-0.221)	(-0.415)
GDP Growth	-0.0613***	-0.0546**	
	(-0.0447)	(-0.0398)	
Central Bank Interest Rate	0.00170**	0.00143	
	(0.0372)	(0.0312)	
DEA		-0.0164	
		(-0.0109)	
Market Share		-0.0354	
		(-0.0374)	
Observations	183	183	183
Number of institutions	26	26	26

Robust normalized beta coefficients in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3b

Determinants of Non-Performing Loans (2015–2019)

	Arellano Bond Estimation		
	(1)	(2)	(3)
	Model 1	Model 2	Model 3
	NPL Ratio	NPL Ratio	NPL Ratio
NPL Lagged	-0.0290	-0.00326	-0.00112
	(-0.0280)	(-0.00326)	(-0.00111)
DEAR		-0.0260	
		(-0.0150)	
Market ShareR		-0.0462	
		(-0.0532)	
Leverage	-0.0106	-0.00118	2.65e-07
	(-0.415)	(-0.0551)	(1.24e-05)
GDP Growth		-0.0158**	
		(-0.00683)	
Central Bank Interest Rate		0.0102***	
		(0.0219)	
DEA	0.0704***		0.0309***
	(0.0400)		(0.0214)
Market Share	0.184		-0.0169
	(0.165)		(-0.0156)
Observations	183	74	74
Number of institutions	26	25	25

Robust normalized beta coefficients in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3c

Determinants of Non-Performing Loans (2020–2024)

	Arellano Bond Estimation		
	(1)	(2)	(3)
	Model 1	Model 2	Model 3
	NPL Ratio	NPL Ratio	NPL Ratio
NPL Lagged	-0.00112	1.502***	1.444***
	(-0.00111)	(1.424)	(1.369)
DEAR		0.0802*	
		(0.0551)	
Market ShareR		-0.0439	
		(-0.0443)	
Leverage	2.65e-07	0.00169	0.00296
	(1.24e-05)	(0.0592)	(0.104)
GDP Growth		-0.0803*	
		(-0.0671)	
Central Bank Interest Rate		-0.000532	
		(-0.0136)	
DEA	0.0309***		0.0443
	(0.0214)		(0.0220)
Market Share	-0.0169		-0.127
	(-0.0156)		(-0.113)
Observations	74	109	109
Number of institutions	25	25	25

Robust normalized beta coefficients in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3d

Significance Tests for Models 1, 2, and 3

Test for Model 1

	Statistic	p-value
Arellano–Bond AR(1) (first differences)	$z = -1.44$	0.150
Arellano–Bond AR(2) (first differences)	$z = 0.26$	0.792
Hansen overidentification test	$\chi^2(2) = 1.50$	0.472

Notes: AR tests are based on first-differenced residuals. The null hypothesis of no second-order serial correlation is not rejected. The Hansen test is robust to heteroskedasticity.

Test for Model 2

	Statistic	p-value
Arellano–Bond AR(1) (first differences)	$z = -0.22$	0.830
Arellano–Bond AR(2) (first differences)	$z = -0.26$	0.798
Hansen overidentification test	$\chi^2(2) = 1.57$	0.456

Notes: AR tests are based on first-differenced residuals. The Hansen test is robust to heteroskedasticity.

Test for Model 3

	Statistic	p-value
Arellano–Bond AR(1) (first differences)	$z = -0.97$	0.331
Arellano–Bond AR(2) (first differences)	$z = 0.97$	0.332
Hansen overidentification test	$\chi^2(2) = 1.64$	0.439

Table 3a-c shows that leverage[26] is non-relevant variable. Another indicator of the bank's risk behavior, measured based on its market share (relative or absolute), was not significant. Our sample includes large banks for each country in the LA region.

The DEA or variable that captures efficiency and bank management was significant with the non-expected sign. An increase in efficiency reduces operational costs and rises non-performing loans. These results only apply to relative and absolute efficiency measures. A higher level of bank efficiency measured by Data Envelopment Analysis may be associated with higher non-performing loans when efficiency gains are driven by aggressive credit expansion rather than improved risk management[27]. Hence, market power is not relevant in determining delinquency.

For this sample, the two external variables, GDP growth and the central bank interest rate, had heterogeneous results. For the sample 2015–2019, before pandemic the effect of interest rate was positive–so increase in interest rate rises NPLS. The drop of interest rate in pandemic period did not affect NPLs. On the other hand, for all the periods, GDP growth reduced NPLs which is an expected sign since macroeconomic factors can influence loan quality. Likewise, lagged delinquency was significant with a negative sign[28].

[26] For all model specifications.

[27] The construction of DEA permits this result.

[28] In the Arellano Bond Estimation, this is an instrumental variable that helps us to provide consistent estima-

4. Conclusions

We explored the determinants of delinquency using panel data from the top five banks in Latin America. Some internal factors, such as leverage and management (DEA), are relevant in explaining delinquency. Efficient management of inputs to produce bank outputs is significant and reduces delinquency. Bank efficiency should be measured relative to the full sample rather than with a single country. This means that the bank's relative power is not relevant; rather, absolute efficiency, which is obtained when we rank banks within the full panel sample.

Leverage showed a sign contrary to what was expected. We anticipated an increase in leverage level or an increase in the share of loans in the system to reflect aggressive risk-taking behavior, implying a greater willingness to take on bad loans. However, this was not the case, which means that the region's top five banks (large banks in the sample) adopt a more conservative policy, as they comply with the Basel framework.[29]

External factors such as GDP growth showed a mainly negative effect, which is consistent with findings in the existing literature. An increase in GDP reduces delinquency, and NPLs decline. Further research could include an assessment of smaller banks over the same period: before and after the pandemic.

This paper is relevant to explore determinants of NPLs and also to monitor Bank Efficiency which is widely used in the financial literature as a predictor of bankruptcy. This allows bankers to pinpoint specific sources of inefficiency, such as excess operating costs or suboptimal resource allocation, and to assess how much performance could improve without increasing inputs. As a result, efficiency analysis complements traditional financial ratios and supports strategic decisions aimed at improving competitiveness, profitability, and long-term sustainability.

Analyzing non-performing loans is highly relevant for policymakers because it provides early signals of financial system vulnerabilities and credit misallocation. As we have seen in our paper discussion, elevated or rising NPL ratios reflect weaknesses in lending standards, borrower solvency, or macroeconomic conditions, which can threaten banking sector stability and amplify economic downturns.

tions.

[29] Smaller banks find it difficult to comply with the Basel framework.

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