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The Macroeconomic Impact on Bank's Portfolio Credit Risk: The Colombian Case

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ABSTRACT

This paper explores the determinants of credit risk for the Colombian economy, a small emerging economy in Latin American. Using a sample of 28 large banks over the 2009–2019 period and the dynamic data panel approach, we find that the macroeconomic environment's deterioration affects the credit risk perception held by banks as measured through non-performing loans and loan loss provisions. On the other hand, a better political environment brought about by peace accords smoothed such an impact. Estimates indicate different reactions when distinguishing by loan type. Business credit depends heavily on unemployment, while consumer credit risk is more sensitive to the interest rate. In the case of mortgage loans, economic growth and the unemployment rate are the most critical variables to mitigate risk. These results shed light on the impact of the economic environment on credit lines with different features.

KEYWORDS
Credit risk; banking; emerging economies

JEL
C23; G21; F41

1. Introduction

The current economic recession caused by the COVID-19 pandemic has drawn attention to the consequences it may have on the banking system. As a result, there is great interest in knowing which indicators can provide efficient signals about financial instability (Chau, Lin, and Lin 2020). Loan performance is an essential channel to analyze the effect that macroeconomic factors have on banking crises. Unfavorable economic conditions such as lower economic growth and high unemployment can increase loan defaults and bankruptcies, so the issue of the procyclicality of the financial system should attract the attention of both academics and policymakers because it can exacerbate the economic downturn (Castro 2013: Cecchetti and Kohler 2014; De Moraes and De Mendonça 2019).

Credit risk is the main channel for relating economic shocks to bank balance sheets. It is defined as the risk that a loan will not be paid (partially or totally) to the lender and it is a problem that has received extensive theoretical research. The seminal paper of Altman and Saunders (1998) initially surveyed the approaches that existed on the subject. Credit risk analyses have changed from so-called banking expert systems analyses to more objective schemes. Until the late 1980s, bankers used microeconomic information on the borrower such as reputation, capital, ability to pay, and collaterals to make subjective judgments about credit risk. By the late 1990s, these models began to fail because they did not consider the economic environment in which banks operate. New approaches began to explore alternatives to explain credit risk based on the possible states of the economy. In particular, the study by Salas and Saurina (2002) pioneered this issue by combining micro and macroeconomic data to assess credit risk.

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The literature on banking suggested two hypotheses about credit risk. The first hypothesis indicates that the increase in non-performing loans is due to inefficient management at the banks such as low quality in selecting borrowers, information problems, among others (Jiménez and Saurina 2006; Memmel, Gündüz, and Raupach 2015; Podpiera and Weill 2008). The second hypothesis comes from recent literature that considers credit risk associated with macroeconomic factors (Bayar 2019; Castro 2013; Duarte, Marias, and Azzim 2020; Nkusu 2011; Quagliarello 2007). We followed this stream of literature, although the focus is on macroeconomic conditions and their possible effects on credit risk.

Most of the studies that have analyzed credit risk have done so for Europe and the United States, but the issue is of greater importance in developing countries where bank failures are more recurrent and macroeconomic instability is higher. In the case of Latin America, the limited availability of deposits as a source of funding for banks makes the supply of credit more sensitive to economic friction (Restrepo 2019). In fact, loans are the main asset for banks and the alternative forms of funding are quite limited (Cantú, Claessens, and Gambacorta 2022). Despite these characteristics, studies about credit risk faced by banks in Latin American countries are still scarce, and it is possible that the macroeconomic and political instability of the region could explain the low development of credit, and the financial markets frictions (De Mendonça and Barcelos 2015).

This study aims to contribute to the literature that analyzes the relationship between credit risk with the economic environment in which banks operate in emerging economies. In particular, the intent is to determine the factors that explain credit risk in Colombia. Colombia is the fourth largest economy in Latin America, overcoming a serious financial crisis in the late 1990s. After this, the country adopted its inflation targeting scheme, set fiscal rules, and achieved an investment grade for the first time in its history in 2014 (Cao-Alvira and Palacios-Chacón 2019). The country has also followed the macroprudential regulatory policies that have been promoted by the Basel III accords for reaching macro-financial stability (BCBS 2014). Moreover, the increase of financial deepening after the peace agreement in 2016 (Colombia had 50 years of civil war), in a banking system dominated by only a few banks (Galvis and Hincapié 2018), made the Colombian case an interesting study case of credit risk behavior in emerging economies.

In order to evaluate the macroeconomic determinants of credit risk in Colombia, an original database was built with 28 banks from the Colombian economy. Through a dynamic panel analysis, this database sets the stage for concluding that the credit risk by Colombian banks, as measured through non-performing loans and credit provisions, is sensitive to specific macroeconomic variables. The findings show that economic growth, rising unemployment, and the tightening of monetary policy increase credit risk. On the other hand, a better political environment with peace agreements reduce the credit risk and the impact of interest rates on credit risk, smoothing the risk-taking channel. Additionally, the analysis of the loan types improves the understanding of how Colombian banks hold credit risk. Business credit risk depends heavily on unemployment, and the risk of consumer credit is more sensitive to the interest rate. Besides, the results remain robust when the coverage ratio is used as another measure of credit risk.

Often, the literature analyzes the risks of the financial system to break down and affect the economy. However, there is also the opposite causality. This work shows that the economic environment alters credit risk perception and may constrain credit flow for Colombia's economy. Therefore, based on the results of this study, it is possible to suggest strategies in the context of COVID-19 for Colombia's financial system. Support to corporate loans given by the government with its official banks or the purchase of private debt securities by the central bank to provide liquidity to the financial system seems a practical option. To sum up, the increase in credit risk due to challenging economic conditions must be one of the main problems to be solved by the monetary and fiscal authorities to renew growth.

The remainder of this paper is organized as follows. Section 2 analyzes the Colombian financial system and the evolution of credit risk. Section 3 presents an econometric model to evaluate the determinants to credit risk, while in Section 4 the estimates and results are presented with the credit risk determinants being evaluated by types of loans. Finally, Section 5 states the conclusion.

2. The Colombian Financial System

The Colombian financial system went through a strong macro-financial crisis in 1999 that led to the disappearance of half of the financial institutions (Uribe 2013). In the banking sector specifically, while in 1998 there were 38 banks operating, ten years later, in 2008, the reestablishment had been small with only 18 banks operating.

The recovery occurred during the period after the international financial crisis of 2007–2008. Since the subprime crisis, the Colombian financial system has had greater regulation by the Financial Superintendence. Colombian banks improved their profit, solvency, and risk management indicators, which allowed for increasing financial deepening (Uribe 2013). At the same time, after more than 5 years of negotiation, the Colombian government has reached a peace agreement, which came into force in November 2016. It involved the reconstruction and development of the Colombian regions most affected by decades of military conflict (Cao-Alvira and Palacios-Chacón 2019). In reaction to this new environment, credit increased with considerable dynamism in the period of 2011–2019 and is close to reaching 45% of GDP (see Figure 1).

Most loans in Colombia are allocated to businesses (60% on average), followed by consumer loans (27%), and lastly mortgage loans (10%). There are other types of loans that make up for less than 3% of the portfolio (see Figure 2). A slight increase in the participation of consumer and mortgage loans can been observed since 2015. These two types of loans justify more than 80% of the increase in the total loan portfolio in recent years. Consumer loans have been driven by the increased issuance of credit cards, which by 2019 totaled 15 million. For its part, mortgage loans have been promoted by some Colombian government housing programs.

The possible relationship between the economic and political environment and credit growth made Colombia an exciting laboratory to analyze credit risk behavior. To do so it is necessary to analyze the behavior of banks of different sizes and characteristics while considering the heterogeneity that each bank presents to the macroeconomic outlook and their different managerial profiles in order to analyze credit risk.

According to the empirical literature, the credit risk held by banks can be measured by two variables: the ratio of Non-Performing Loans (*NPL*) to total loans and Provisions (*PROV*), which are measured by loan loss provisions/gross loans ratio (De Moraes and De Mendonça 2019). The latter variable represents the expected loss of banks with respect to loans and it is a forward-looking measure of credit risk. According to Figure 3, it is observed that the credit risk presented

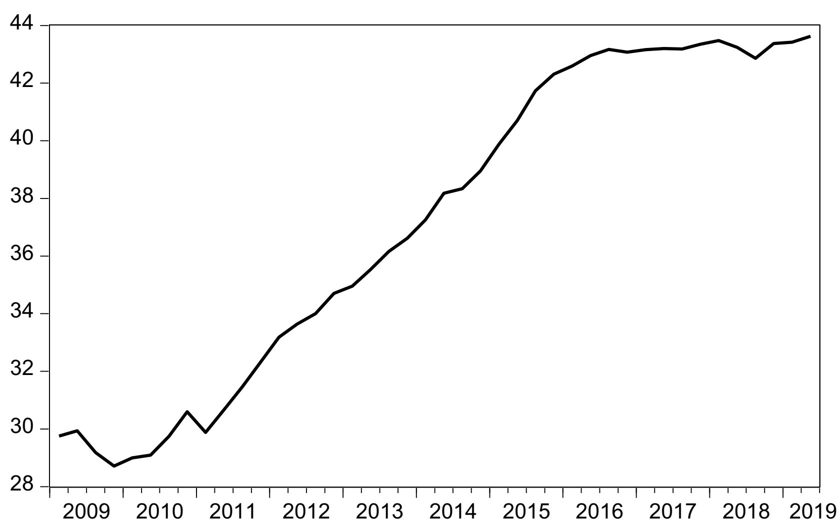

Figure 1. *Financial deepening in Colombia* (Credit/GDP in %).

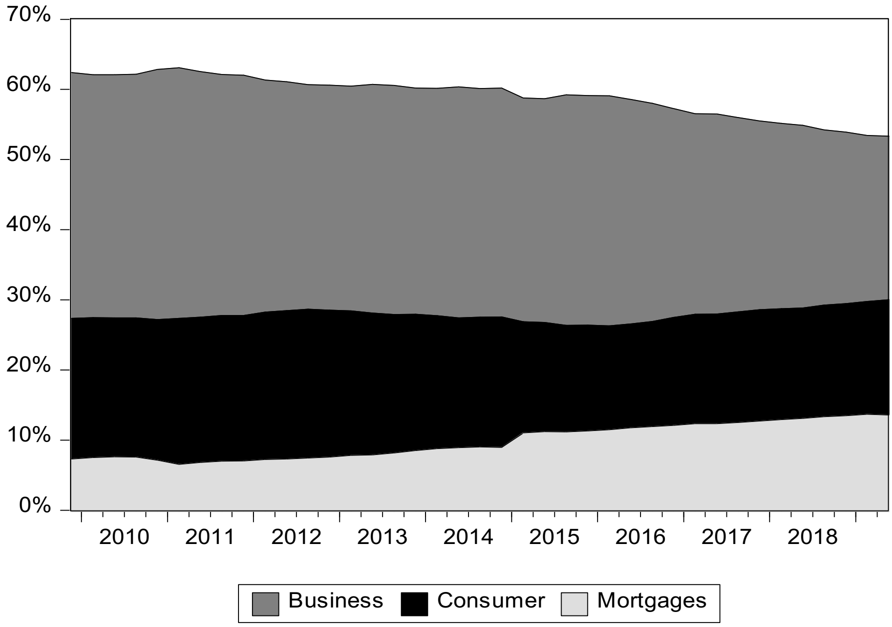

Figure 2. Loans by type.

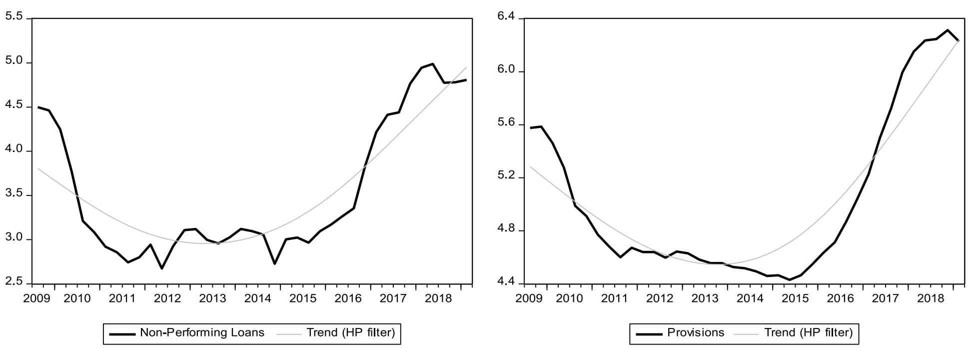

Figure 3. Evolution of credit risk in Colombia.

a tendency to fall between 2009–2013 in both measurements. Then, credit risk began to rise in 2014 and peaked in late 2018. The central hypothesis of this study is that the perception of credit risk by banks can be explained by the instability of the economic and political environment in Colombia.

3. Methodology

In general, macroeconomic conditions play an essential role in addressing credit risk. As pointed by Jiménez and Saurina (2006), Quagliarello (2007), Nkusu (2011), Castro (2013), and Bayar (2019), lower economic growth results in less income, which leads agents to have problems with paying their loans. Thus, the annualized real GDP growth (*GDP*) is used as the first variable to explain credit risk. The unemployment rate affects the generation of consumer cash flow and may increase the default rate of the loan. Consequently, following Castro (2013) and Ghosh (2015), we used the unemployment rate as a second variable to explain credit risk (*UNEMPLOYMENT*). Finally, the risk-taking channel explains how monetary policy interest rate affects credit risk (Diamond and Rajan 2011; Bonfim and Soares 2018; De Moraes and De Mendonça 2019). Considering this, we used the monetary policy rate (*INTEREST*) as a third macroeconomic variable.

Credit risk also depends on the bank-specific characteristics. Following Jiménez and Saurina (2006), Podpiera and Weill (2008), and Memmel, Gündüz, and Raupach (2015), three bank-specific variables need to be considered in a bank's heterogeneity: return on assets (*ROA*), liquidity (*LIQ*), and size (*SIZE*). In the case of Colombia, there is no data to associate loans with idiosyncratic characteristics of each firm or agent, but it is possible to associate the position of firms with their stock market performance (see Bonfim 2009; Castro 2013; Nkusu 2011). It is expected that the increase in equity prices will be related to improvements in the financial balance of the companies, impacting their ability to pay a loan. From this we use the behavior of the Colombian Stock Exchange (*COLCAP*) index as another explanatory variable of the credit risk.

Following the recent empirical studies of bank behavior, we adopt a dynamic panel data analysis to consider the time persistence in credit risk, to which we used a lagged dependent in our model as such as De Moraes and De Mendonça (2019). Besides, as Castro (2013) and Louzis, Vouldis, and Metaxas (2012), we considered the credit risk growth, NPL, and provisions, becoming the basis for the following model:

$$\Delta y_{i,t} = \beta_0 \Delta y_{i,t-1} + \sum_{j=1}^{3} \rho_j X_{j,t-1} + \sum_{k=1}^{3} \gamma_k Z_{i,t-1}{}^{k} + \varepsilon_{i,t} \tag{1}$$

where $i = 1, \ldots, 28$ denotes the number of banks and $t = 2009Q1, \ldots, 2019Q2$ the quarterly data. $y_{i,t}$ denotes the credit risk measured by Non-Performing Loans (*NPL*) and Provisions (*PROV*), X_j denotes the macroeconomic variables (*GDP, UNEMPLOYMENT, INTEREST, COLCAP*), $Z_{i,t}$ are the bank-specific variables (*ROA, LIQ, SIZE*), and $\varepsilon_{i,t}$ is the error term. Table 1 shows the descriptive statistics.[1]

In order to avoid spurious results, we ran the unit root tests for panel by Levin, Lin, and Chu (2002), Im, Pesaran, and Shin (2003), and the Fischer-ADF test that assumes individual unit root processes. The tests are presented in Table A.2 (Appendix) where the null hypothesis is that there are unit-roots. The results show that all series used in the basic model are stationary.

The use of a dynamic data panel assists in eliminating the problem of unobserved effects, which leads to regression estimates being biased by the presence of omitted variables (Arellano and Bond 1991). However, due to possible endogeneity problems between the model variables and the error term, OLS estimates (POLS, FE, and RE) are not consistent for a dynamic panel. To minimize this problem, we used the System-GMM (S-GMM) as proposed by Arellano and Bover (1995) and Blundell and Bond (1998).

To avoid the possible problems of consistency in the parameters, Arellano and Bover (1995) and Blundell and Bond (1998) indicated the lagged variables of the model in first differences as instruments, which allow for greater consistency in the estimated parameters. In addition, the S-GMM estimator uses standardized residuals to build a consistent variance-covariance matrix, thus using the 2-stage estimation method. Given this, the Sargan over-identification test is calculated to confirm the

Table 1. Descriptive statistics.

Variable	Mean	Median	Maximum	Minimum	St. dev
NPL	0.0467	0.0432	0.2263	0.0071	0.0254
PROV	0.0582	0.0537	0.3655	0.02125	0.0275
GDP	0.0370	0.0312	0.0100	0.0867	0.0181
UNEMPLOYMENT	0.0963	0.0948	0.1180	0.0824	0.0093
INTEREST	0.0456	0.0450	0.0775	0.0300	0.0127
COLCAP	1534.32	1548.98	1832.75	1153.71	174.775
ROA	0.0152	0.0165	0.1763	−0.3411	0.0261
LIQ	0.1745	0.0924	1.3031	0.0013	0.2278
SIZE	14.5914	14.1620	18.6861	9.4827	1.9331

validity of the instruments used.[2] The AR autocorrelation test was also estimated to validate the assumptions about the error term. We also estimated an approximation to the Breusch-Pagan-Godfrey (BPG) heteroscedastic test. For this, the squared residuals were taken and these were regressed against the variables of each model. The results showed that there are no heteroscedasticity problems.

4. Estimates and Results

Table 2 shows the estimates of the basic model with the reported findings suggesting that macroeconomic variables matter when explaining the non-performing loan and credit provisions, which means macroeconomic conditions impact the credit risk held by Colombian banks. The coefficient associated with *GDP* was negative and significant. This result confirmed the hypothesis that indicates that credit risk is procyclical. Less dynamism in the economy creates difficulties for both consumers and companies to pay their obligations, which is reflected in the increases in non-performing loans and provisions. Similar results were reported by Jiménez and Saurina (2006), Quagliarello (2007), Nkusu (2011), Castro (2013), and Bayar (2019).

The unemployment rate also provides essential information about economic conditions and the borrower's ability to pay. As can be seen in Table 2, the coefficient associated with the unemployment rate (*UNEMPLOYMENT*) is positive and significant. In line with findings from Nkusu (2011) and Ghosh (2015), the fall in income followed by the rise in unemployment is reflected in a growth in non-performing loans rates and in a demand for higher provisions. In the Colombian case, unemployment stops the primary source of income for families and creates difficulties for them to meet their debts (see Gutiérrez and Vásquez, 2008).

As for the monetary policy rate (*INTEREST*), the results indicated that the associated coefficient is positive and significant. Besides, estimates of the complete model suggested that this coefficient had the most significant impact on non-performing loans and provisions. This means that the credit risk in Colombia is affected by the risk-taking channel. When the central bank raises the short-term interest rate, the debt service coverage ratio for households and firms increases, thus boosting the likelihood of loan defaults (Altunbas et al. 2010). Estimates also show that stock market performance matters. The coefficient associated with *COLCAP* is negative and significant. This evidence allows inferring that increases in the price of the main Colombian shares decrease the probability of default on loans. Similar results for other economies are reported by Bonfim (2009), Nkusu (2011) and Castro (2013).

The coefficient associated with the return on assets (*ROA*) is negative and significant and, as a result, the good management hypothesis is confirmed. This result indicates that greater managerial efficiency is related to better selection of borrowers, lower loans in default, and therefore a lower credit risk (see Jiménez and Saurina 2006; Podpiera and Weill 2008; Bonfim 2009; Memmel, Gündüz, and Raupach 2015).

The results also indicate that the coefficient associated with the size of the banks (*SIZE*) is not always significant. However, the findings seem to indicate that larger banks do make higher provisions. Finally, the coefficient associated with liquidity (*LIQ*) is positive and statistically significant in the estimation models. Banks that are more liquid may have incentives to change their risk-taking behavior and ease their loan requirements. Thus, the results indicate that more liquid banks are likely to take more risks and have more defaulted loans (see, for example, Bonfim and Soares 2018).

4.1. Credit Risk by Loan Type

According to Louzis, Vouldis, and Metaxas (2012), it is important to verify possible differences in the determinants of credit risk based on the type of loan. In the case of the Colombian economy, statistics allow differentiation between consumer, business, and mortgage loans. With these series, credit risks can be computed for each type of loan portfolio (see Figure 4).

Table 2. Empirical determinants of credit risk for Colombia.

	Non-Performing Loans (*NPL*)					Provisions (*PROV*)				
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Δy_{it-1}	−0.2752***	−0.2865***	−0.2590***	−0.2691***	−0.1948***	0.4259***	0.2650***	0.3436***	0.5835***	0.3587***
	(0.0045)	(0.0042)	(0.0132)	(0.0057)	(0.0108)	(0.03409)	(0.0086)	(0.0070)	(0.0035)	(0.0095)
	[−60.2280]	[−67.5634]	[−19.5485]	[−46.813]	[18.005]	[12.4947]	[30.5360]	[48.6152]	[162.2891]	[37.6465]
GDP_{t-1}	−0.0548***				−0.0330***	−0.0670***				−0.0434***
	(0.0037)				(0.0058)	(0.0056)				(0.0066)
	[−14.5163]				[−5.6595]	[−13.4577]				[−6.5702]
$UNEMPLOYMENT_{t-1}$		0.0667***			0.0917***		0.0798***			0.0682***
		(0.0060)			(0.0084)		(0.0058)			(0.0079)
		[10.9988]			[10.8434]		[10.1707]			[8.5649]
$INTEREST_{t-1}COLCAP_{t-1}$			0.1373***	−3.28E-06***	0.1217***			0.0882***	−6.92E-06***	0.1122***
			(0.0056)	(2.36E-07)	(0.0123)			(0.0122)	(7.31E-07)	(0.0156)
			[24.4745]	[−13.923]	[9.8700]			[7.1947]	[−9.4690]	[7.1592]
					-8.24E-07**					-2.87E-06***
					(3.30E-07)					(5.78E-07)
					[−2.4997]					[−4.9642]
ROA_{it-1}	−0.0319***	−0.0456***	−0.0334**	−0.0330***	−0.0304**	−0.1244***	−0.2374***	−0.3328***	−0.1759***	−0.2122**
	(0.0098)	(0.0090)	(0.0175)	(0.0088)	(0.0118)	(0.0309)	(0.0276)	(0.0211)	(0.0256)	(0.0303)
	[−3.2537]	[−5.0704]	[−1.9094]	[−3.7414]	[−2.5632]	[−4.0207]	[−8.5895]	[−15.7607]	[−6.8659]	[−7.0014]
$LIQ_{i,t-1}$	0.0207***	0.0154***	0.0377***	0.0047**	0.0281***	0.0396***	0.0109***	0.0184***	0.0008	0.0240**
	(0.0049)	(0.0034)	(0.0070)	(0.0017)	(0.0076)	(0.0029)	(0.0037)	(0.0026)	(0.0050)	(0.0119)
	[4.1998]	[4.5298]	[−5.3350]	[2.6997]	[3.6942]	[13.4048]	[2.9152]	[6.8236]	[0.1795]	[2.0062]
$SIZE_{i,t-1}$	−0.0005	0.0022***	0.0045***	−0.0018	−0.0002	0.0119***	0.01598***	0.0109***	0.0479***	0.0042***
	(0.0005)	(0.0004)	(0.0175)	(0.0022)	(0.0013)	(0.0003)	(0.0011)	(0.0006)	(0.0007)	(0.0015)
	[−0.9417]	[5.0683]	[−1.9094]	[−0.8173]	[−0.1671]	[30.9596]	[13.5201]	[16.3828]	[61.6718]	[2.7069]
J-stat	25.52	25.79	25.38	25.86	24.28	26.86	26.37	25.33	26.83	24.78
Sargan test (p-value)	0.32	0.31	0.33	0.30	0.23	0.26	0.28	0.28	0.26	0.20
AR(1)	−0.46	−0.48	−0.47	−0.47	−0.47	−0.60	−0.56	−0.59	−0.54	−0.60
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	−0.04	−0.01	−0.00	−0.04	−0.03	0.03	0.02	0.04	0.06	−0.04
p-value	0.22	0.64	0.79	0.22	0.26	0.34	0.51	0.21	0.77	0.21
F-statistic (BPG)	0.24	0.46	0.19	0.43	0.79	0.12	0.30	0.38	0.11	0.16
Number of Instruments	27	27	27	27	27	29	28	28	27	28
Observations	922	922	922	922	866	922	922	922	922	866

Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors between parentheses. S-GMM uses Arellano and Bond (1991) without time period effects. Tests AR(1) and AR(2) check that the average autocovariance of the residuals are zero. In all specifications, p-values show that GMM results are consistent. F-statistic (BPG) denotes the p-value significance of the Breusch-Pagan-Godfrey heteroscedasticity test. The sample is an unbalanced panel of 28 financial institutions.

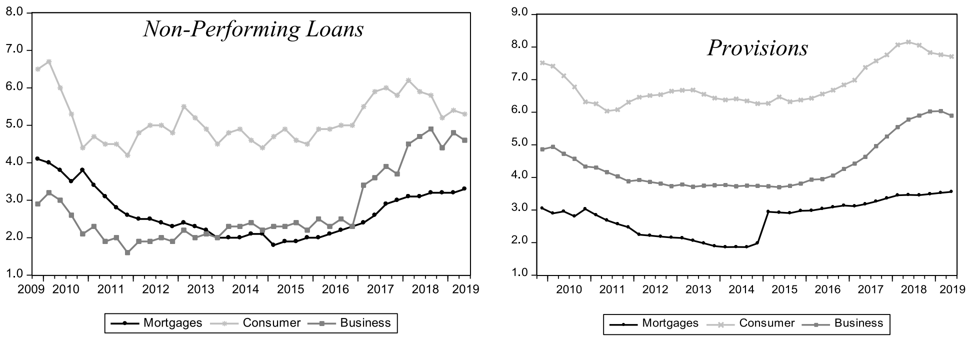

Figure 4. Credit risk by type of loan.

As previously noted, the credit risk was lower for mortgage loans for the period 2009–2019 with the consumer credit presenting the highest risk. Commercial loans ranked in the middle. However, since 2016 the credit risk of these loans is increasing as evidenced by the increase in both the NPL and their provisions. Based on the heterogeneity observed in the credit risk by loan type, we re-estimated the basic model for each loan type using the GMM method. The results are presented in Tables 3–5.

Since the variables *GDP, UNEMPLOYMENT*, and *INTEREST* are in the same units of measurement (see Table 1) and the standard errors are close to zero, it is possible to make comparisons. In the case of the results of the full model with NPL, in consumer loans the parameter associated with *INTEREST* was 0.0878 and the parameter of *UNEMPLOYMENT* 0.0383. In the case of business loans, the parameters were 0.0326 for *INTEREST* and 0.0702 for *UNEMPLOYMENT*. Finally, in the case of mortgages, the *INTEREST* parameter was 0 and the *UNEMPLOYMENT* parameter 0.0218. In the case of the parameter associated with *GDP*, for consumer loans the parameter was −0.0284, in the case of business it was −0.0092, and for mortgages −0.0289. Thus, similarly with the results of Louzis, Vouldis, and Metaxas (2012), the sensitivities of credit risk by types of loans against macroeconomic variables are different.

The results denote that consumer loan default is affected to a greater extent by the unemployment rate (*UNEMPLOYMENT*) and interest rates (*INTEREST*). In fact, the parameters associated with the interest rate on these loans are the largest. It is important to highlight that consumer loans can be charged the so-called usury rates or maximum admissible rate. This finding denotes that it is possible that usury rates increase the debt burden in an accelerated way and, consequently, the default risk.

For business loans, the econometric results show that the most critical parameter is associated with the unemployment rate (*UNEMPLOYMENT)* because these loans are aimed primarily at companies. The weakened labor market performance may affect the cash flow of the firms through the aggregate demand of consumers, thus unemployment growth brings lower sales and leads firms not to meet their loan duties. Similar findings are reported by Louzis, Vouldis, and Metaxas (2012).

From the case of mortgage loans, the risk is explained by the unemployment rate (*UNEMPLOYMENT*) and economic growth (*GDP*). It is important to point out that these loans are agreed at a fixed interest rate and are long term, consequently the interest rate is not the main variable to explain the mortgage credit risk, and its coefficient is close to zero or not significant, meaning that adverse economic conditions associated with lower family income, consequences of a low economic growth and the weakened labor market, have the most significant impact on non-performing mortgage loans.

In the last macro-financial variable, the coefficient associated with the stock market's behavior (*COLCAP*) shows the same signs and magnitudes found before without distinguishing by type of loan. The parameters associated with the bank-specific variables also show differences between the different types of loans. In particular, return on assets (*ROA*) is found to be important in mitigating credit risk on mortgage and business loans. In the case of consumer loans, the signs of the parameter are positive

Table 3. Empirical determinants of credit risk for Colombia: Consumer loans.

	Non-Performing Loans					Provisions				
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Δy_{it-1}	−0.3454*** (0.0043) [−80.282]	−0.3921*** (0.0014) [−279.243]	−0.3448*** (0.0087) [−39.270]	−0.3381*** (0.0070) [−48.087]	−0.3010*** (0.0156) [−19.218]	0.8086*** (0.0048) [166.8328]	−0.6623*** (0.0252) [26.2884]	0.7397*** (0.0067) [108.9025]	0.7760*** (0.0047) [163.2347]	0.8078*** (0.0174) [46.4231]
GDP_{t-1}	−0.0311*** (0.0014) [−21.305]				−0.0284*** (0.0023) [−10.573]	−0.0190*** (0.0004) [−4.5177]				−0.0128*** (0.0038) [−3.3651]
$UNEMPLOYMENT_{t-1}$		0.1067*** (0.0020) [52.501]			0.0383*** (0.0093) [4.0995]		0.0780*** (0.0145) [5.3578]			0.0772*** (0.0119) [6.4855]
$INTEREST_{t-1}$			0.1024*** (0.0074) [13.800]		0.0878*** (0.0121) [7.2641]			0.0483*** (0.0057) [8.3608]		0.0834*** (0.0234) [3.5632]
$COLCAP_{t-1}$				−3.27E-06*** (3.17E-07) [−10.318]	−4.01E-06*** (6.16E-07) [−6.5097]				−3.73E-06*** (5.41E-07) [−6.8903]	−2.59E-06*** (7.34E-07) [−3.5250]
ROA_{it-1}	0.0305*** (0.0114) [−3.1057]	0.0505*** (0.0149) [−5.3245]	0.0500*** (0.0044) [−11.195]	0.0491*** (0.0112) [−4.4491]	0.0301 (0.0362) [−1.0790]	0.0190*** (0.0072) [2.6200]	0.1048*** (0.0400) [2.6159]	0.1770*** (0.0331) [5.3396]	0.0853*** (0.0048) [17.5966]	0.0455*** (0.0172) [2.6387]
$LIQ_{i,t-1}$	0.0482*** (0.0026) [18.105]	0.0184*** (0.0003) [61.092]	0.0315*** (0.0030) [10.344]	0.0309*** (0.0041) [7.3837]	0.0368*** (0.0069) [5.2780]	0.0721*** (0.0012) [56.001]	0.1311*** (0.0113) [11.5551]	0.1008*** (0.0024) [40.9425]	0.0741*** (0.0028) [14.5696]	0.0088*** (0.0019) [4.5300]
$SIZE_{i,t-1}$	0.0035*** (0.0008) [43.250]	0.0030*** (0.0005) [52.816]	0.0007*** (0.0074) [13.800]	0.0001*** (0.0002) [4.6191]	3.60E-05 (0.0004) [0.0738]	0.0133*** (0.0034) [3.8522]	0.0180** (0.0072) [2.4961]	0.0008* (0.0005) [1.6487]	0.0072*** (0.0003) [20.9305]	0.0028** (0.0013) [2.0741]
J-stat	21.76	26.20	22.36	20.81	17.91	27.02	25.17	25.80	24.43	24.82
Sargan test (p-value)	0.53	0.29	0.50	0.57	0.59	0.25	0.34	0.30	0.38	0.20
AR(1)	−0.49	−0.48	−0.57	−0.56	−0.50	−0.54	−0.50	−0.54	−0.54	−0.57
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	−0.01	−0.05	0.04	0.02	−0.04	0.08	0.06	0.08	0.09	0.07
p-value	0.76	0.12	0.17	0.46	0.15	0.10	0.15	0.11	0.10	0.11
F-statistic(BPG)	0.19	0.69	0.34	0.50	0.13	0.84	0.46	0.26	0.14	0.40
Number of Instruments	27	27	27	27	27	28	28	28	28	28
Observations	952	952	952	952	952	952	952	952	952	952

Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors between parentheses. S-GMM uses Arellano and Bond (1991) without time period effects. Tests AR(1) and AR(2) check that the average autocovariance of the residuals are zero. In all specifications, p-values show that GMM results are consistent. F-statistic (BPG) denotes the p-value significance of the Breusch-Pagan-Godfrey heteroscedasticity test. The sample is an unbalanced panel of 28 financial institutions.

Table 4. Empirical determinants of credit risk for Colombia: Business loans.

	Non-Performing Loans					Provisions				
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Δy_{it-1}	−0.2550***	−0.2085***	−0.2398***	−0.2142***	−0.1616***	0.7668***	0.4936***	0.7428***	0.6084***	0.8297***
	(0.0029)	(0.0033)	(0.0018)	(0.0040)	(0.0030)	(0.0042)	(0.0210)	(0.0070)	(0.0161)	(0.0117)
	[−85.026]	[−63.178]	[−132.88]	[−53.211]	[−52.865]	[179.8661]	[23.4972]	[105.4424]	[37.5690]	[70.3717]
GDP_{t-1}	−0.0349***				−0.0092***	−0.0193***				−0.0093***
	(0.0010)				(0.0013)	(0.0027)				(0.0018)
	[−32.740]				[−6.7320]	[−7.0000]				[−5.1456]
$UNEMPLOYMENT_{t-1}$		0.0787***			0.0720***		0.0295***			0.1125***
		(0.0032)			(0.0087)		(0.0089)			(0.0099)
		[23.033]			[8.2628]		[2.7572]			[11.3553]
$INTEREST_{t-1}$			0.0507***		0.0326***			0.0193***		0.0280***
			(0.0008)		(0.0025)			(0.0052)		(0.0091)
			[89.096]		[12.980]			[5.2160]		[3.0664]
$COLCAP_{t-1}$				−3.98E-07**	−1.61E-06***				−1.16E-05***	−1.90E-06***
				(1.99E-07)	(2.75E-07)				(6.77E-07)	(4.29E-07)
				[−2.0028]	[−5.8472]				[−17.1292]	[−4.4204]
ROA_{it-1}	−0.0394***	−0.0432***	−0.0553***	−0.0552***	−0.0434***	−0.1061***	−0.1807***	−0.0478**	−0.1759***	−0.0758**
	(0.0111)	(0.0057)	(0.0023)	(0.0118)	(0.0082)	(0.0187)	(0.0154)	(0.0198)	(0.0212)	(0.0319)
	[−3.5287]	[−6.369]	[−6.5904]	[−4.6760]	[−5.3040]	[−5.6466]	[−11.6927]	[−2.4049]	[−8.2742]	[−2.3749]
$LIQ_{i,t-1}$	−0.0055***	−0.0264***	−0.0068***	−0.0253***	−0.0008	−0.0067***	−0.0129***	−0.0048***	−0.0345***	−0.0075***
	(0.0012)	(0.0020)	(0.0003)	(0.0025)	(0.0006)	(0.0018)	(0.0021)	(0.0017)	(0.0012)	(0.0014)
	[4.5920]	[13.171]	[−20.027]	[−10.106]	[−1.2082]	[−3.6913]	[6.0127]	[−2.8568]	[−28.0483]	[−5.0816]
$SIZE_{i,t-1}$	0.0250***	0.0147***	0.0203***	0.0141***	0.0315***	0.0049***	0.0423***	0.0340***	0.0265***	0.0491***
	(0.0008)	(0.0006)	(0.0006)	(0.0022)	(0.0014)	(0.0005)	(0.0023)	(0.0022)	(0.0031)	(0.0041)
	[30.671]	[22.312]	[29.4007]	[6.2204]	[21.957]	[8.7663]	[18.0571]	[15.2777]	[8.3512]	[11.8845]
J-stat	24.01	27.02	29.56	24.59	23.58	26.37	24.81	23.13	26.85	23.61
Sargan test (p-value)	0.40	0.25	0.16	0.37	0.26	0.23	0.35	0.45	0.26	0.25
AR(1)	−0.52	−0.54	−0.64	−0.53	−0.56	−0.47	−0.43	−0.48	−0.43	−0.53
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	0.01	0.04	0.01	−0.01	0.02	0.01	0.02	0.02	0.02	0.05
p-value	0.90	0.19	0.99	0.73	0.45	0.81	0.55	0.82	0.58	0.46
F-statistic(BPG)	0.17	0.36	0.14	0.51	0.17	0.31	0.19	0.08	0.89	0.53
Number of Instruments	27	27	27	27	27	27	27	27	27	27
Observations	952	952	952	952	952	952	952	952	952	952

Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors between parentheses. S-GMM uses Arellano and Bond (1991) without time period effects. Tests AR(1) and AR(2) check that the average autocovariance of the residuals are zero. In all specifications, p-values show that GMM results are consistent. F-statistic (BPG) denotes the p-value significance of the Breusch-Pagan-Godfrey heteroscedasticity test. The sample is an unbalanced panel of 28 financial institutions.

Table 5. Empirical determinants of credit risk for Colombia: Mortgage loans.

	Non-Performing Loans					Provisions				
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Δy_{it-1}	−0.3057***	−0.1952***	−0.3954***	−0.3400***	−0.3890***	0.8949***	0.7959***	0.8028***	0.8004***	0.8747***
	(0.0074)	(0.0052)	(0.0089)	(0.0427)	(0.1190)	(0.0007)	(0.0011)	(0.0005)	(0.0026)	(0.0018)
	[−41.166]	[−37.307]	[−44.163]	[7.9561]	[−3.2671]	[122.894]	[−67.8358]	[16.0538]	[30.3994]	[47.6659]
GDP_{t-1}	−0.0395***				−0.0289***	−0.0254***				−0.0320***
	(0.0011)				(0.0038)	(0.0007)				(0.0017)
	[−34.055]				[−7.4663]	[−36.2659]				[−18.7269]
$UNEMPLOYMENT_{t-1}$		0.0368***			0.0218**		0.2091***			0.2877***
		(0.0034)			(0.0112)		(0.0054)			(0.0151)
		[10.711]			[1.9663]		[38.5129]			[18.9734]
$INTEREST_{t-1}$			0.0062***		0.0013			0.0080***		0.0034*
			(0.0013)		(0.0086)			(0.0024)		(0.0054)
			[4.4747]		[1.5743]			[3.5913]		[1.7888]
$COLCAP_{t-1}$				−2.15E-06***	−8.49E-07***				−8.68E-06***	−3.62E-06***
				(7.76E-07)	(3.58E-07)				(3.71E-07)	(3.79E-07)
				[−2.7656]	[−2.3733]				[−23.4270]	[−9.5588]
ROA_{it-1}	−0.1167***	−0.0494***	−0.3339***	−0.2537***	−0.0933***	−0.1382***	−0.0391***	−0.0189***	−0.0687***	−0.2352***
	(0.0033)	(0.0016)	(0.0077)	(0.0115)	(0.0315)	(0.0093)	(0.0037)	(0.0004)	(0.0032)	(0.0091)
	[−34.956]	[−30.393]	[−42.929]	[−21.948]	[−2.9623]	[−25.5761]	[−10.4705]	[−20.9666]	[−20.9989]	[−25.58]
$LIQ_{i,t-1}$	0.0065***	0.0063***	0.0051***	0.0140**	0.0232***	0.0002	0.0137***	0.0035***	0.0097***	0.0105***
	(0.0017)	(0.0005)	(0.0003)	(0.0057)	(0.0046)	(0.0001)	(0.0002)	(0.0007)	(0.0004)	(0.0020)
	[3.6509]	[12.168]	[16.669]	[2.4593]	[4.9622]	[1.4454]	[55.1704]	[4.9490]	[23.9644]	[5.2010]
$SIZE_{i,t-1}$	0.0024***	0.0035***	0.0039***	0.0047***	0.0044***	0.0151***	0.0117***	0.0093***	0.0163***	0.0047***
	(0.0003)	(0.0004)	(0.0005)	(0.0007)	(0.0005)	(0.0012)	(0.0002)	(0.0004)	(0.0004)	(0.0003)
	[8.0346]	[72.706]	[78.077]	[6.4595]	[8.1422]	[12.4919]	[43.7701]	[20.9668]	[36.7819]	[12.8696]
J-stat	14.96	14.01	16.96	11.74	11.57	19.99	20.18	19.65	19.28	16.73
Sargan test (p-value)	0.38	0.52	0.47	0.62	0.39	0.27	0.26	0.29	0.31	0.27
AR(1)	−0.49	−0.55	−0.34	−0.38	−0.43	−0.55	−0.55	−0.55	−0.54	−0.56
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	−0.00	0.08	−0.08	−0.02	−0.06	0.06	0.04	0.05	0.03	0.06
p-value	0.87	0.07	0.08	0.49	0.15	0.22	0.27	0.57	0.53	0.13
F-statistic(BPG)	0.09	0.96	0.15	0.40	0.28	0.92	0.97	0.62	0.96	0.23
Number of Instruments	19	19	20	20	20	22	22	22	22	22
Observations	527	527	527	527	527	952	952	952	952	952

Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors between parentheses. S-GMM uses Arellano and Bond (1991) without time period effects. Tests AR(1) and AR(2) check that the average autocovariance of the residuals are zero. In all specifications, p-values show that GMM results are consistent. F-statistic (BPG) denotes the p-value significance of the Breusch-Pagan-Godfrey heteroscedasticity test. The sample is an unbalanced panel of 28 financial institutions.

and therefore good managerial performance would not reduce risk. Mortgage and business loans are long-term and of significant magnitude, hence the banking system must classify users well to avoid moratoriums that leave large debts for the system. Thus, the evidence indicates that entities with more considerable managerial skills classify agents better and, therefore, present a lower default risk. To sum up, better-managed banks have better clients and lower default rates in mortgage and business loans. A similar finding is reported by Quagliarello (2007).

The results indicate that the parameters associated with size (*SIZE*) is significant and positive for all types of credit, but the parameter is essential to explain the risk only in the case of business and mortgage loans, while in consumer loans the parameter is significant but close to zero. These findings allow us to indicate that larger banks face higher credit risks when setting up business and mortgage loans and should be monitored to avoid banking crises. In the case of the parameter associated with liquidity (*LIQ*), a different result was found for business loans where the parameter, surprisingly, has a positive sign. In these cases, the parameter is negative and significant. Thus, greater liquidity is associated with less credit risks. This evidence indicates that business loans may be viewed as profitable opportunities for banks and substitutes for other investments. Therefore, banks take more considerable precautions when providing business loans because they compromise their liquidity and expected profitability. In the case of consumer and mortgage loans, the results found in the previous session are confirmed.

4.2. Further Results

To capture the peace agreement's possible effect on credit risk, we added a dummy variable (*DUMMY_PA*) to the model for 2016-Q4, which is the moment when the peace agreements were signed in Colombia. Despite Non-Performing loans and Provisions being measures of credit risk used in this study, only Non-Performing loans is considered a proxy of financial stability, according to Horváth and Vasko (2016). Therefore, we tested the hypotheses that the political stability provided by the peace agreement can impact financial stability as measured by Non-Performing loans. For that we included the dummy variable on equation (1).

The results on Table 6 show the dummy variable's negative and significant coefficient indicating that the signing of the peace agreements may have reduced Non-Performing loans. This result suggests that political stability expectations can improve financial stability. Besides, when it interacts with the monetary policy interest rate (*DUMMY_PA*INTEREST*), the negative and significant sign of the parameter indicates that the peace agreements reduced the impact of a risk-taking channel on Colombian banks. This result reinforced the effects of the political environment on credit risks held by banks.

4.3. Robustness Analyses

In order to confirm our results, we followed Alessi et al. (2020) and estimate a model with a new credit risk proxy (dependent variable), the coverage ratio (*COV*). De Mendonça and De Moraes (2018) pointed out that coverage ratio is calculated as a ratio of loan loss provisions to non-performing loans.

In general, the results presented in Table 7 reveal the same results as the previous sections. According to the econometric results, the coverage ratio responds inversely with *GDP* and positively with *UNEMPLOYMENT*. Moreover, the *COV* decreases during booms and increases during recessions, creating a procyclical behavior in coverage. By the way, *INTEREST* is positive and significant. Therefore, monetary policy can influence the quality of assets and the banks' credit risk with banks making higher provisions under tighter monetary conditions. Finally, in the case of the bank-specific variables, the results are similar to those reported before.

Table 6. Empirical results of credit risk for Colombia: Non-Performing Loans.

	Non-Performing Loans							
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Δy_{it-1}	−0.2573*** (0.0076) [−33.4477]	−0.2777*** (0.0138) [−20.0850]	−0.2118*** (0.0131) [−16.1015]	−0.2516*** (0.0121) [−20.7980]	−0.2573*** (0.0076) [−33.4477]	−0.2777*** (0.0138) [−20.0850]	−0.2118*** (0.0131) [−16.1015]	−0.1276*** (0.0115) [−11.0415]
GDP_{t-1}	−0.0568*** (0.0047) [−12.0229]				−0.0568*** (0.0047) [−12.0229]			−0.0281*** (0.0073) [−3.8266]
$UNEMPLOYMENT_{t-1}$		0.0602*** (0.0128) [4.6768]				0.0602*** (0.0128) [4.6768]		0.1468*** (0.0132) [11.0630]
$INTEREST_{t-1} COLCAP_{t-1}$			0.1769*** (0.0073) [23.9147]	−6.00E-06*** (2.25E-07) [−26.6511]			0.1769*** (0.0073) [23.9147]	0.0917*** (0.0084) [10.8434] -3.41E-07** (4.07E-07) [−0.8386]
$Dummy\_PA_t$	−0.0018*** (0.0002) [−6.2798]	−0.0003 (0.0004) [−0.8757]	−0.0085*** (0.0002) [−30.4935]	−0.0007*** (0.0001) [−4.6141]				−0.0088*** (0.0004) [−20.9290]
$Dummy\_PA_t * GDP_{t-1}$					−0.0804*** (0.0128) [−6.2798]			
$Dummy\_PA_t * UNEMPLOYMENT_{t-1}$						0.0952 (0.1087) [0.8757]		
$Dummy\_PA_t * Interest_{t-1}$							−0.1146*** (0.0037) [−30.4935]	
$COLCAP_{t-1}$				−6.00E-06*** (2.25E-07) [−26.6511]				−1.19E-0.6* (6.37E-07) [−1.8731]
ROA_{it-1}	−0.0481*** (0.0248) [−1.9372]	−0.0550*** (0.0181) [−3.0322]	−0.0984*** (0.0174) [−5.6391]	−0.0495** (0.0206) [−2.4020]	−0.0481*** (0.0248) [−4.3720]	−0.0550*** (0.0181) [−3.0322]	−0.0984*** (0.0174) [−5.6391]	−0.0694*** (0.0158) [−4.3720]
$LIQ_{i,t-1}$	0.0199*** (0.0048) [4.0714]	0.0146*** (0.0039) [3.6955]	0.0377*** (0.0070) [−5.3350]	0.0263** (0.0027) [9.4812]	0.0199*** (0.0048) [4.0714]	0.0146*** (0.0039) [3.6955]	0.0377*** (0.0070) [−5.3350]	0.0285*** (0.0082) [3.4746]
$SIZE_{i,t-1}$	−0.0004 (0.0005) [−0.9255]	0.0021*** (0.0004) [4.7776]	0.0045*** (0.0175) [−1.9094]	−0.0051 (0.0035) [−1.4738]	−0.0004 (0.0013) [−0.1533]	0.0021*** (0.0004) [4.7776]	0.0045*** (0.0175) [−1.9094]	−0.0002 (0.0013) [−0.1533]

(*Continued*)

Table 6. (Continued).

	Non-Performing Loans							
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
J-stat	25.45	25.39	25.38	25.01	25.45	25.39	25.38	24.17
Sargan test (p-value)	0.27	0.27	0.33	0.29	0.27	0.27	0.33	0.18
AR(1)	−0.46	−0.48	−0.47	−0.47	−0.46	−0.48	−0.47	−0.47
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	−0.04	−0.01	−0.00	−0.03	−0.04	−0.01	−0.00	−0.03
p-value	0.22	0.64	0.79	0.22	0.22	0.64	0.79	0.26
F-statistic(BPG)	0.31	0.84	0.28	0.73	0.61	0.19	0.89	0.19
Number of Instruments	27	27	27	27	28	28	28	27
Observations	922	922	922	922	922	922	922	866

Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors between parentheses. S-GMM uses Arellano and Bond (1991) without time period effects. Tests AR(1) and AR(2) check that the average autocovariance of the residuals are zero. In all specifications, p-values show that GMM results are consistent. F-statistic (BPG) denotes the p-value significance of the Breusch-Pagan-Godfrey heteroscedasticity test. The sample is an unbalanced panel of 28 financial institutions.

Table 7. Empirical determinants of coverage ratio for Colombia.

	Coverage				
Regressors	Model 1	Model 2	Model 3	Model 4	Model 5
Δy_{it-1}	−0.3145*** (0.0143) [−21.8765]	−0.3308*** (0.0099) [−33.3315]	−0.3380*** (0.0149) [−22.6887]	−0.3182*** (0.0087) [−36.5238]	−0.3224*** (0.0147) [−21.8045]
GDP_{t-1}	−1.3945*** (0.1460) [−9.5504]				−1.8053*** (0.4102) [−4.4000]
$UNEMPLOYMENT_{t-1}$		2.0075*** (0.5136) [3.9084]			2.1858*** (0.5084) [4.2988]
$INTEREST_{t-1}COLCAP_{t-1}$			2.4968*** (0.4988) [5.0047]	−0.0001*** (1.91E-05) [−7.9493]	2.9011* (1.6653) [1.7420] -9.96E-05*** (2.51E-05) [−3.9615]
ROA_{it-1}	1.6222** (0.6873) [2.3599]	0.9464*** (0.3081) [3.0711]	2.5389*** (0.6341) [4.0035]	2.3277*** (0.5600) [4.1562]	1.2605** (0.4848) [2.5999]
$LIQ_{i,t-1}$	−8.40E-05 (0.2103) [−0.0003]	0.3302*** (0.1207) [2.7352]	0.3828 (0.4279) [0.8946]	0.2162 (0.1604) [1.3477]	0.0657 (0.1184) [0.5546]
$SIZE_{i,t-1}$	0.1117*** (0.0246) [4.5239]	0.1614*** (0.0224) [7.1943]	0.1029** (0.0468) [2.1963]	0.2015*** (0.0326) [21.4899]	0.1314*** (0.0311) [4.2256]
J-stat	26.95	26.86	25.49	26.54	24.13
Sargan test (p-value)	0.25	0.26	0.32	0.27	0.23
AR(1)	−0.47	−0.45	−0.41	−0.46	−0.45
p-value	0.00	0.00	0.00	0.00	0.00
AR(2)	−0.00	−0.06	−0.08	−0.04	−0.01
p-value	0.93	0.19	0.12	0.15	0.58
F-statistic(BPG)	0.50	0.69	0.34	0.96	0.30
Number of Instruments	28	28	28	27	28
Observations	922	922	922	922	922

Marginal significance levels: (***) denotes 0.01, (**) denotes 0.05, and (*) denotes 0.1. Standard errors between parentheses. S-GMM uses Arellano and Bond (1991) without time period effects. Tests AR(1) and AR(2) check that the average autocovariance of the residuals are zero. In all specifications, p-values show that GMM results are consistent. F-statistic (BPG) denotes the p-value significance of the Breusch-Pagan-Godfrey heteroscedasticity test. The sample is an unbalanced panel of 28 financial institutions.

5. Conclusions

The global economic crisis is paying attention to the problems it can bring to the financial system. In this sense, this study analyzed the effect of macroeconomic perspectives on credit risk for the Colombian case. Through a dynamic data panel approach for the period 2009–2019, it was found that the macroeconomic environment is the primary determinant of Colombia's credit risk. Credit risk increases with declines in GDP growth, rising unemployment, and tightening monetary policy rates.

In 2020 the Colombian economy entered a severe recession and, according to the results of this study, credit risk is likely to increase. In terms of economic policy, this means a threat to financial stability and the possibility of a credit crunch (Louzis, Vouldis, and Metaxas 2012), so different incentives for each type of loan are needed to recover the financial system. Government endorsements and mortgage subsidy policies can help mitigate financial market failures.

Finally, the Central Bank of Colombia must commit to maintaining easy liquidity conditions. These measures can help cushion the increased credit risk in the banks' portfolio. In short, the Colombian financial system is sensitive to the economic situation, which indicates the need to soften the macroeconomic impact on the credit market in Colombia.

Notes

1. See Table A.1 (Appendix) for data sources and a description of the variables.
2. According to De Moraes and De Mendonça (2019), to avoid the excessive use of instruments and the loss of reliability of the tests, the number of instruments used was less than the number of cross-sections.

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References

Alessi, L., B. Bruno, E. Carletti, and K. Neugebauer. 2020. *What drives bank coverage ratios evidence from Europe*. Luxembourg: Publications Office of the European Union.

Altman, E., and A. Saunders. 1998. Credit risk measurement: Developments over the last 20 years. *Journal of Banking & Finance* 21 (11–12):1721–42. doi:10.1016/S0378-4266(97)00036-8.

Altunbas, Y., L. Gambacorta, and D. Marques-Ibanez. 2010. Bank risk and monetary policy. *Journal of Financial Stability* 6 (3):121–29. doi:10.1016/j.jfs.2009.07.001.

Arellano, M., and S. Bond. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58 (2):277–97. doi:10.2307/2297968.

Arellano, M., and O. Bover. 1995. Another look at the instrumental variables estimation of error components models. *Journal of Econometrics* 68 (1):29–51. doi:10.1016/0304-4076(94)01642-D.

Bayar, Y. 2019. Macroeconomic, institutional and bank-specific determinants of non-performing loans in emerging market economies: A dynamic panel regression analysis. *Journal of Central Banking Theory and Practice* 8 (3):95–110. doi:10.2478/jcbtp-2019-0026.

BCBS – Basel Committee on Banking Supervision. 2014. *Basel III leverage ratio framework and disclosure requirements*. Basel Committee on Banking Supervision, Bank for International Settlements.

Blundell, R., and S. Bond. 1998. Initial conditions and moment conditions in dynamic panel data models. *Journal of Econometrics* 87 (1):115–43. doi:10.1016/S0304-4076(98)00009-8.

Bonfim, D. 2009. Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics. *Journal of Banking & Finance* 33 (2):281–99. doi:10.1016/j.jbankfin.2008.08.006.

Bonfim, D., and C. Soares. 2018. The risk-taking channel of monetary policy: Exploring all avenues. *Journal of Money, Credit, and Banking* 50 (7):1507–41. doi:10.1111/jmcb.12500.

Cantú, C., S. Claessens, and L. Gambacorta. 2022. How do bank-specific characteristics affect lending? New evidence based on credit registry data from Latin America. *Journal of Banking and Finance* 135 (February): 105818.

Cao-Alvira, J. J., and L. A. Palacios-Chacón. 2019. Financial deepening and business creation: A regional analysis of Colombia. *Emerging Markets Finance & Trade* 55 (4):1–16.

Castro, V. 2013. Macroeconomic determinants of the credit risk in the banking system: The case of the GIPSI. *Economic Modelling* 31 (C):672–83. doi:10.1016/j.econmod.2013.01.027.

Cecchetti, S., and M. Kohler. 2014. When capital adequacy and interest rate policy are substitutes (And When They Are Not). *International Journal of Central Banking* 10 (3):205–31.

Chau, M., C. Lin, and T. Lin. 2020. Wisdom of crowds before the 2007–2009 global financial crisis. *Journal of Financial Stability* 48 (C):100741. doi:10.1016/j.jfs.2020.100741.

De Mendonça, H., and V. Barcelos. 2015. Securitization and credit risk in the Brazilian economy. *The North American Journal of Economics and Finance* 32 (2):12–28. doi:10.1016/j.najef.2015.01.002.

De Mendonça, H., and C. De Moraes. 2018. Central bank disclosure as a macroprudential tool for financial stability. *Economic Systems* 42 (4):625–36. doi:10.1016/j.ecosys.2018.07.001.

De Moraes, C., and H. De Mendonça. 2019. Bank's risk measures and monetary policy: Evidence from a large emerging economy. *North American Journal of Economics and Finance* 49 (3):121–32. doi:10.1016/j.najef.2019.04.002.

Diamond, D. W., and R. G. Rajan. 2011. Fear of fire sales, illiquidity seeking, and credit freezes. *The Quarterly Journal of Economics* 126 (2):557–91. doi:10.1093/qje/qjr012.

Duarte, F., A. Marias, and M. Azzim. 2020. Credit risk, owner liability, and bank loan maturities during the global financial crisis. *European Financial Management* 26 (3):628–83. doi:10.1111/eufm.12239.

Galvis, J. C., and G. Hincapié. 2018. Effect of Banking Concentration on the Lending Channel: Evidence from Colombia. *Economic Bulletin* 38 (4):2254–65.

Ghosh, A. 2015. Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability* 20 (C):93–104. doi:10.1016/j.jfs.2015.08.004.

Gutiérrez, J., and D. Vásquez. 2008. Un Análisis de Cointegración para el Riesgo de Crédito. Financial Stability Report, September. Central Bank of Colombia, 1–18.

Horváth, R., and D. Vasko. 2016. Central bank transparency and financial stability. *Journal of Financial Stability* 22:45–56. doi:10.1016/j.jfs.2015.12.003.

Im, K. S., M. H. Pesaran, and Y. Shin. 2003. Testing for unit roots in heterogeneous panels. *Journal of Econometrics* 115 (1):53–74. doi:10.1016/S0304-4076(03)00092-7.

Jiménez, G., and J. Saurina. 2006. Credit cycles, credit risk and prudential regulation. *International Journal of Central Banking* 2 (2):65–98.

Levin, A., C. F. Lin, and C. S. J. Chu. 2002. Unit root tests in panel data: Asymptotic and finite sample properties. *Journal of Econometrics* 108 (1):1–24. doi:10.1016/S0304-4076(01)00098-7.

Louzis, D., A. Vouldis, and V. Metaxas. 2012. Macroeconomic and bank-specific determinants of nonperforming loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking and Finance* 36 (4):1012–27. doi:10.1016/j.jbankfin.2011.10.012.

Memmel, C., Y. Gündüz, and P. Raupach. 2015. The common drivers of default risk. *Journal of Financial Stability* 16 (C):232–47. doi:10.1016/j.jfs.2014.03.002.

Nkusu, M. 2011. Nonperforming loans and macrofinancial vulnerabilities in advanced economies. IMF Working Papers 11/161, International Monetary Fund.

Podpiera, J., and L. Weill. 2008. Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability* 4 (2):135–48. doi:10.1016/j.jfs.2008.01.005.

Quagliarello, M. 2007. Banks' riskiness over the business cycle: A panel analysis on Italian intermediaries. *Applied Financial Economics* 17 (2):119–38. doi:10.1080/09603100500486501.

Restrepo, F. 2019. The effects of taxing bank transactions on bank credit and industrial growth: Evidence from Latin America. *Journal of International Money and Finance* 93 (C):335–55. doi:10.1016/j.jimonfin.2019.02.005.

Salas, V., and J. Saurina. 2002. Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research* 22 (3):203–24. doi:10.1023/A:1019781109676.

Uribe, J. D. 2013. El sistema financiero colombiano: Estructura y evolución reciente. *Revista Banco de la República* 1023:5–17.

Appendix

Table A.1. Sources of data and description of the variables.

	Type	Variable	Definition	Source
Dependent Variable	i	NPL_{it}	Bank non-performing loans to total gross loans	Financial Superintendence of Colombia https://www.superfinanciera.gov.co/inicio/evolucion-cartera-de-creditos-60950
	i	$PROV_{it}$	Provisions. Measured by loan loss provisions/ gross loans ratio	Financial Superintendence of Colombia https://www.superfinanciera.gov.co/inicio/evolucion-cartera-de-creditos-60950
	i	COV_{it}	Coverage ratio. Computed by loan-loss provisions/ NPL ratio	Financial Superintendence of Colombia https://www.superfinanciera.gov.co/inicio/evolucion-cartera-de-creditos-60950
Macroeconomic Determinants	c	*GDP*	Growth of real GDP	Central Bank of Colombia http://www.banrep.gov.co/es/estadisticas/producto-interno-bruto-pib
	c	*UNEMPLOYMENT*	Unemployment rate	Central Bank of Colombia http://www.banrep.gov.co/es/estadisticas/tasas-empleo-y-desempleo
	c	*INTEREST*	Monetary policy rate	Central Bank of Colombia http://www.banrep.gov.co/es/estadisticas/tasas-interes-politica-monetaria
	c	*COLCAP*	Colombia's stock market index	Central Bank of Colombia http://www.banrep.gov.co/es/estadisticas/mercado-accionario
Bank-specific variables	i	*ROA*	Return on assets (%). Profit before Tax/Total Assets	Financial Superintendence of Colombia https://www.superfinanciera.gov.co/inicio/indicadores-gerenciales-niif-10084493
	i	*liq*	Ratio of liquid assets to total assets	Financial Superintendence of Colombia https://www.superfinanciera.gov.co/jsp/60951
	i	*SIZE*	Log of total bank assets	Financial Superintendence of Colombia https://www.superfinanciera.gov.co/jsp/60949

C or i stand respectively for "common to all banks" or "bank-specific variable."

Table A.2. Unit root tests Levin-Lin-Chu, Im-Pesaran-Shin, and Fisher-ADF.

	Levin-Lin-Chu		Im-Pesara-Shin		ADF-Fischer	
Series	Statistic	Prob.	Statistic	Prob	Statistic	Prob
ΔNPL	−6.1382	0.0000	−4.2268	0.0000	112.576	0.0000
ΔPROV	−3.7541	0.0000	−22.9259	0.0000	553.120	0.0020
ΔCOV	−4.9891	0.0000	−4.0269	0.0000	100.505	0.0000
GDP	−9.14361	0.0000	−21.257	0.0000	460.484	0.0000
UNEMPLOYMENT	−16.700	0.0000	−37.686	0.0000	943.843	0.0000
INTEREST	−4.0469	0.0000	−2.9284	0.0017	74.083	0.0050
COLCAP	−6.1148	0.0000	−16.1662	0.0000	330.197	0.0000
ROA	−9.7145	0.0000	−10.2268	0.0000	233.288	0.0000
LIQ	−10.3856	0.0000	−8.2250	0.0000	184.290	0.0000
SIZE	−1.5360	0.0600	−2.4493	0.0072	81.9399	0.0135

Tests were developed with individual effects and individual linear trends. Automatic lag difference term and bandwidth selection (using the Schwarz criterion for the lag differences and the Newey-West method and the Bartlett kernel for the bandwidth).