Can The Level Of The Monetary Policy Rate Alter The Bank Lending Channel? Evidence From An Emerging Market

SUMMARY

This paper examines the impact of Colombia's sharp monetary policy shifts between 2016 and 2023 on the bank lending channel (BLC) in a small emerging economy. During this period, the policy rate fluctuated by 11.5 percentage points, from a pandemic-induced low to a historic peak in early 2023. Leveraging a novel quantile regression approach, we analyze how these fluctuations influence the BLC across different segments of the credit market. Our findings confirm the presence of the BLC across all percentiles, though its effect weakens at higher percentiles. Furthermore, key bank characteristics—such as liquidity, size, and capitalization—play a crucial role in shaping the BLC, with varying effects depending on the type of credit considered.

JEL: E51, E58

Key words: bank lending channel, dynamic panel.

1. INTRODUCTION

Recently Colombia's financial intermediaries have faced sharp contrasts in macro-financial conditions in a short period of time. Since the declaration of a pandemic in March 2020, the Colombian financial system faced significant challenges arising from the containment and the greater materialization of financial and non-financial risks (particularly credit risk) on the balance sheet of credit institutions, which led to recourse to the flexibility of prudential regulation to provide relief to affected debtors.

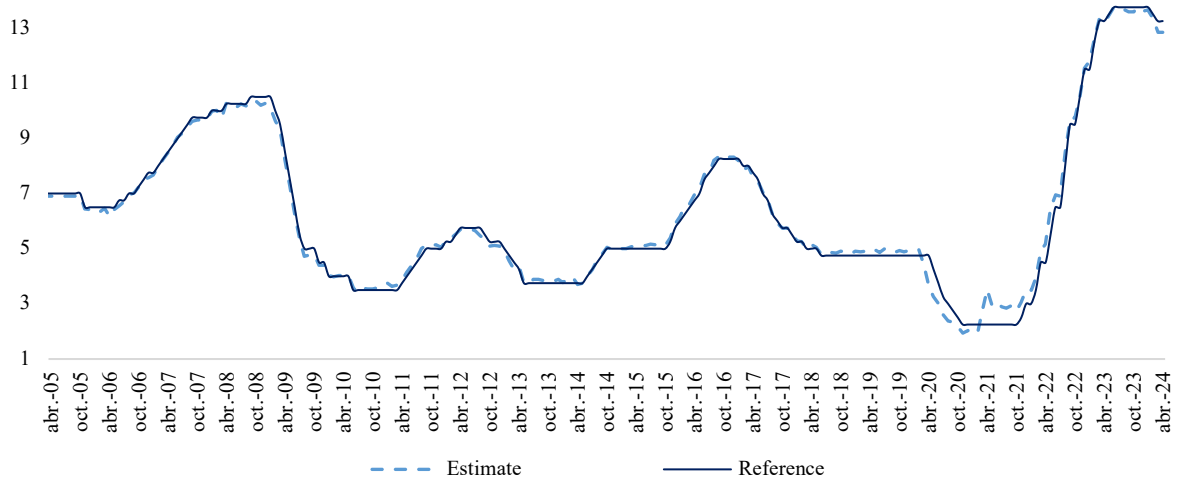
The persistence and depth of the shock led to rapid action by the central bank to reduce your interest rate to a low of 1.75% in September of that year, to exert a counter-cyclical boost and favor liquidity conditions. Broadly expansionary monetary conditions contributed to a rapid recovery of economic

growth in 2021, which allowed normalizing the monetary policy stay reaching 3% at the end of this year and start a gradual dismantling of the relief package to debtors.

The expectation of accelerated growth in 2022 contrasted with the surprise start of tensions between Russia and Ukraine, which quickly escalated to transmit to the global economy as a supply shock. Inflation in Colombia was strongly influenced by this external shock and added to the strong dynamism of domestic demand brought it to historically high levels, in May it reached 9.1% higher than the historical record and surprised closing year at 13.1%. The monetary policy rate also reached historic records reaching 12% in December 2022.

Inflation peaked in March 2023 (13.3%) and the monetary policy ceiling was reached shortly thereafter in May 2023 (13.25%). In a period of just over 24 months, Colombia faced the historic minimum and maximum of the monetary policy rate (a range of 11.75 pp). In fact, as Figure 1 shows, 83% of the distribution of the monetary policy rate analyzed between January 2006 and April 2024 (220 months) is between 2.6% and 9.8%, less than 14% corresponds to the ranges between 2.6% and over 9.8%.

Figure 1. Monetary policy rate



Source: own elaboration, based on Colombia Central Bank

In Colombia, the evidence for BLC is strong, but it has not been evaluated -as far as we know- for this limiting behavior of the monetary policy rate, and how it could interact with the balance sheet of credit institutions and other macroeconomic factors. This work follows Apergis and Christou (2015), who

employ a quantile regression approach to study the BLC and the effect of considering the entire distribution of the monetary policy rate, so that we can observe not only the typical effect on the average, but local effects for different percentiles considered.

Contrary to Apergis and Christou (2015), who finds that the BLC is present only in the average for Europe, our analysis shows that the BLC is present in all percentiles and types of loans in Colombia. This result is robust to different control variables, such as bank liquidity, size and capitalization. In addition, we found decreasing effects of the BLC as the percentile increases, suggesting that the BLC depends on the distribution of the variables -median and mean- regressions are quite different. In fact, we confirm that the evidence for Colombia also depends on the magnitude of policy change during this period and reiterate the importance of the distribution of policy rates in the middle of the COVID and post-pandemic period.

This document begins with this introduction. Section 2 presents the BLC and the empirical literature s findings about it. Section 3 shows the results of the estimation. Section 4 concludes.

2. EVIDENCE FOR THE BLC

The bank lending channel (BLC) suggests that banks play a special role in the transmission of monetary policy. As monetary policy affects banks' funding costs, it impacts banks' lending conditions. Bernanke and Gertler (1995) identify three conditions for the existence of the BLC: (i) imperfect and incomplete credit markets that do not allow perfect substitution between internal and external sources of funding, (ii) imperfect substitutability between deposits and other bank liabilities, and (iii) imperfect substitutability between loans and other forms of external financing for firms. Moreover, the empirical literature has shown that the BLC depends on banks' liquidity, capitalization, and size.

Many papers point to a pass-through of monetary policy to BLC, varying by country and depending on the characteristics of credit institutions. For instance, Altunbas, Fazylov and Molyneux (2002) find support for the BLC for European Monetary Union countries. They observe that banks with lower levels of capitalization tend to respond more to monetary policy changes, especially in the smallest countries in the sample –Spain and Italy.

For Europe, Altunbas, Gambacorta and Marquez-Ibañez (2009) find evidence of the BLC by analyzing securitization and off-balance sheet operations during the 2008 financial crisis. In addition, Gambacorta and Marques-Ibañez (2011), for a sample of European countries, show that banks with lower levels of capital, high dependence on market funding and without income diversification are more sensible to the BLC.

For Eastern European economies, Matousek and Sarantis (2009) find that the main determinants of the BLC are banks´ size and short-term liquidity. Joyce and Spaltro (2014) and Cahn, Duquerroy and Mullins (2017), find that the Bank of England's quantitative easing (QE) policy during the 2008 crisis had a positive effect on credit growth and asset prices.

For the Netherlands, Ees, Garretsen and Sterken (1999) examine the BLC in an open economy context. They observe heterogeneous effects due to banks' liquidity and size, and that the BLC is lower as banks demand for bonds and term-deposits is higher. Likewise, Haan (2003) finds evidence of the BLC using a dynamic panel and identifies asymmetries in the monetary policy transmission by loans´ size, maturity, and segment, and absence of the BLC for insured credit.

For Italy, Gambacorta (2005) supports the existence of the BLC. Banks' liquidity and solvency are relevant, while size and leverage are not. Following Gambacorta (2005) and controlling by credit market segments, Kakes and Sturm (2002) observe evidence of the BLC for Germany mainly in cooperatives and small banks.

Evidence for the BLC in the US is found by Kishan and Opiela (2000) and Kashyap and Stein (2000). The effect decreases as banks have more liquidity, and vice versa. Also, for the US, Kashyap, Stein and Wilcox (1994, 1995) conclude that the BLC depends on banks´ size –higher size implies lower BLC. Moreover, Kashyap and Stein (2004) find that the BLC depends on the economic cycle.

Considering other emerging markets, Pereraa, Ralston and Wickramanayake (2014) analyze Southeast Asia. They report that less liquid and leveraged credit entities are the most affected by the BLC, and that

securitization operations reduce the effect of the BLC. For Malaysia, Zulkhibri (2012) finds that small, less leveraged, and less liquid financial institutions show a higher BLC.

Considering the analysis of the characteristics associated with the interest rate distribution, Apergis and Christou (2015) examine the existence for Europe using percentile regressions, showing that the BLC exists only at the mean. Indeed, the literature also delves into the configurations of monetary rules and their effects on the FCL, Apergis and Alevizopoulou (2012) point to evidence of the BCL under different configurations of monetary policy rules (including the zero lower bound) with the largest effect found under forward-looking rules, suggesting that the level of the rate could be a relevant factor to study versus the implementation of monetary policy and the FCL.

For the Colombian case, Reyes, Gómez and Ojeda (2013) report that the BLC is higher in less liquid and small credit institutions. In addition, Gómez, Kutan, Ojeda and Ortiz (2016) find that the BLC is asymmetric, higher when the central bank is in a contractionary monetary policy rate stay. Other evidence for Colombia of the BLC is associated with the macroprudential impact on credit growth (Gambacorta and Murcia, 2017; Gómez, Lizarazo, Mendoza and Murcia, 2016). To our knowledge, this would be the first study that analyzes the effect of the level of the monetary policy rate on different aspects documented by the literature in Colombia for the BLC.

3. METHODOLOGY AND DATA

The first difficulty to analyze the BLC is to use aggregate data. Kashyap and Stein (1995) point out that the usage of aggregate data is inappropriate because it assumes that the effect of the policy on each bank is homogeneous. Another problem for the identification of the BLC is to distinguish the relative movements of supply and demand of credit, given the possibility of endogeneity. For these reasons, the empirical literature has use panel data and banks' characteristics such as size, liquidity, and capitalization as explanatory factors of the supply side, as they are unconnected to demand.

Assumptions on the identification equation

To quantify the impact of credit guarantee coverage on loan supply, we develop a theoretical model that captures how financial institutions optimize their resource allocation between loan disbursements and alternative investments. This framework allows for the estimation of how changes in guarantees coverage influence credit supply, considering key factors such as funding costs, risk constraints, and monetary policy conditions. In this setting, a financial institution optimizes its profit by allocating resources between loan disbursements (L_d) and alternative investments (I), considering funding costs, risk constraints, and monetary policy conditions. The objective function is:

$$\Pi = r_L L_d \; - \; r_d D \; - \; C(L_d, D) \; - \; C(L_d, R) + r_m I$$

Where:

r_L = loan interest rate.
L_d = loan disbursements (decision variable).
r_D = interest rate on deposits (funding cost).
D = total monthly deposits.
$C(L_d, D)$ = operational and administrative costs.
$\Theta(L_d, R)$ = credit risk cost, which depends on default probability and secured loans (R).
$r_m I$ = opportunity cost of lending, where r_m (monetary policy rate) affects the return on alternative investments.

Since the bank allocates available funds between loan origination and alternative investments (I):

$$L_d + I = D + K$$

Where K is the bank's own capital. Solving for I :

$$I = D + K - L_d$$

Substituting this into the profit function:

$$\Pi = r_L L_d - r_D D - C(L_d, D) - \Theta(L_d, R) + r_m(D + K - L_d)$$

Rearranging:

$$\Pi = (r_L - r_m)L_d - C(L_d, D) - \Theta(L_d, R) + r_m(D + K) - r_D D$$

To find the optimal loan disbursement level (L_d^*), take the first-order derivative of profit with respect to L_d :

$$\frac{\partial \Pi}{\partial L_d} = (r_L - r_m) - C_{L_d} - \Theta_{L_d} = 0$$

Solving for r_L :

$$r_L = r_m + C_{L_d} + \Theta_{L_d}$$

This shows that the equilibrium loan interest rate is determined by:

The monetary policy rate r_m (opportunity cost of funds).

The marginal cost of loan origination C_{L_d} .

The marginal risk cost Θ_{L_d} .

The loan demand function is given by:

$$L_d = g(Y, r_L)$$

$Y = GDP$ (economic activity driving demand).

r_L loan interest rate, which negatively affects demand:

$$\frac{\partial g}{\partial r_L} < 0$$

Substituting the *equilibrium condition* $r_L^* = r_m + C_{L_d} + \Theta_{L_d}$ into the demand function:

$$L_d = g\left(Y, r_m + C_{L_d} + \Theta_{L_d}\right)$$

Approximating by a linear functional form:

$$L_d^* = \beta_0 + \beta_1 Y - \beta_2\left(r_m + C_{L_d} + \Theta_{L_d}\right)$$

Expanding cost and risk components:

$$L_d^* = \beta_0 + \beta_1 Y - \beta_2 r_m - \beta_3 C_{L_d} - \beta_4 \Theta_{L_d}$$

From credit risk theory, we assume:

$$\Theta_{L_d} = f(\delta, \sigma, \lambda)$$

Where:

δ default probability (higher default risk reduces credit supply).

σ bank solvency (higher solvency relaxes credit constraints).

λ proportion of secured loans (higher collateral mitigates risk).

Similarly, the marginal cost of loan origination depends on funding and operational constraints:

$$C_{L_d} = h(s, D)$$

Substituting these into the disbursement equation:

$$L_d^* = \beta_0 + \beta_1 Y - \beta_2 r_m - \beta_3 h(s, D) - \beta_4 f(\delta, \sigma, \lambda R)$$

Approximating with a linear structure:

$$L_d^* = \phi_0 + \phi_1 Y - \phi_2 r_m + \phi_3 s - \phi_4 \delta + \phi_5 \sigma + \phi_6 \lambda - \phi_7 D$$

Where:

ϕ_1 impact of economic activity on loan demand.
ϕ_2 effect of interest rate spread on lending incentives.
ϕ_3 negative impact of default risk on credit supply.
ϕ_4 positive impact of bank solvency.
ϕ_5 mitigating effect of credit guarantees
ϕ_6 effect of deposit availability on loan origination.

It is worth mentioning that data level approximations per bank or data groups improve the accuracy of the measurements by eliminating this assumption from the estimates. As mentioned by Haan (2003), referring to an analytical argument, the challenge of identifying the problems of the bank lending channel. The variable b_3 is the loan interest rate elasticity to loan demand, effect that could be different among banks. In such way the information contained in the heterogeneity of the panel for each L_i can be exploited as a form of identification of the loan and other effects of the BLC, using the 'identification through heterogeneity' mentioned by Gilchrist and Zakrajšek (1998). Regarding the above, if we assumed that x_1 is the bank characteristics vector, the γ variable significance represents the existence of the BLC.

Percentile regression methodology for the BCL

Regarding the identifications equations argument, we follow Apergis and Christou (2015) who mentions that different impacts are to be expected for the BLC depending on the monetary policy rate distribution. We follow their panel percentile estimation to estimate the BLC in Colombia. We use a dynamic long panel[1] model (T>N) as shown in equation [2], where i = 1, ..., N, t = 1, ..., T, N is the number of banks and T the number of time periods and $u_{i,t}$ the error term.

[1] For long panel where T>N, simple panel estimators are biased.

The change in GDP and the inflation rate are incorporated to control for demand factors, Δl_{it} is the change in the logarithm of bank i´s total loans and $\Delta MONPOL_{t-j}(\tau)$ is change of the monetary policy rate proxy derived for each percentile analyzed. Following the literature, we also include interactions between monetary policy and banks' specific characteristics, BC_{t-j} (size, liquidity, capitalization) and allowances. To control for the Covid-19 period, we include a dummy variable between March 2020 and July 2021.

$$\Delta l_{i,t} = \Delta l_{i,t-1} + \sum_{j=1}^{2} \theta_j \, GDP_{t-j} + \sum_{j=1}^{2} \rho_j \, INF_{t-j} + \sum_{j=1}^{2} \eta_j \, \Delta MONPOL_{t-j}(\tau) + \sum_{j=1}^{2} \sigma_j \, BC_{t-j} + \sum_{j=1}^{2} \sigma_j \; Allowances_{t-j} + \sum_{j=1}^{2} \mu_j \, BC_{t-j} * \Delta MONPOL_{t-j}(\tau) + \text{dummy}_t + u_{i,t} \quad [4]$$

As Apergis and Christou (2015) we estimate two models to estimate equation 4. For the model to evaluate the results at the mean (model I), we apply the Feasible Generalized Least Square estimator. For model II, we use the Generalized Percentile Regression estimator proposed by Powell (2022). This estimator uses the traditional panel data estimator in a percentile non-additive effect context and produces unconditional percentile treatment effects even in the presence of additional control variables. Moreover,

The monetary policy rate proxy for each percentile

To estimate the monetary policy rate proxy by percentile, we use Clarida et al. (2000)´s non-linear monetary policy rule [3]. Where *i* is the monetary policy rate in real terms, *x*, the output gap, and π, the difference between the inflation rate and its target.

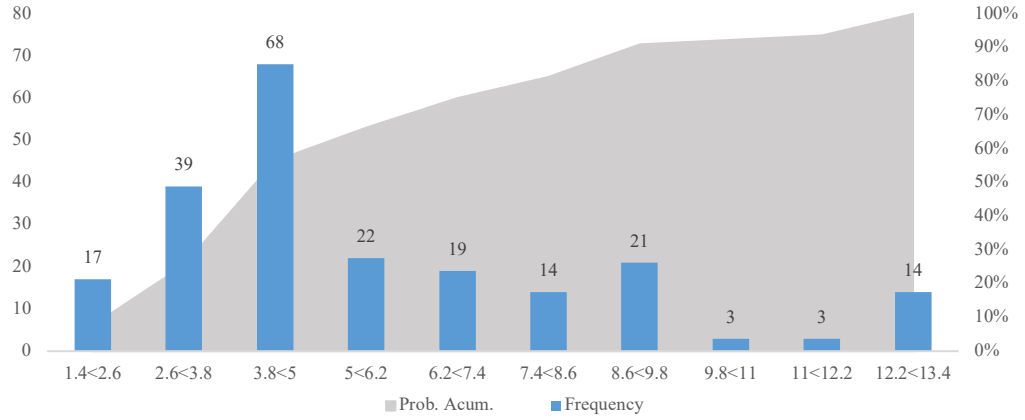
$$i_t = (1-\rho)[\alpha + \beta\pi_t + \gamma y_t] + \rho i_{t-1} + \varepsilon_t \quad [3]$$

We use the same instruments as in Clarida et al. (2000) and estimates the coefficients of the instrumental variables quantile regression (IVQR) model introduced by Chernozhukov & Hansen (2005). We used four lags of the monetary policy rate, the difference between inflation and its target, the output gap, world

commodity price inflation and the slope of the public interest rate curve (21 instruments including the constant), after apply GMM the parameters are shown in equation Table 1.

In Figure 2, we demonstrate the advantages of the nonlinear identification for a forward-looking monetary policy rule, this identification allows us to include future market expectations about monetary policy decisions. We also include some percentiles of the distribution, P10 and P90 for unconditional forecasts, to describe the difference between the (observed) reference rate and synthetic distributions treatments for monetary policy (uncondicioned). This exercise looks directly how the level of monetary policy might affect the measure of the BLC and its interactions with particular bank caracteristics. We extend the same excersise to corporate, consuption and household credit, considering risk apetite behavior for each one could be very different along monetary policy cycle.

Figure 2. Frequency distribution and cumulative probability (right) of monetary policy rate (%)



Source: own elaboration, based on Colombia Central Bank

Description of the data

The data sample consists of 14 banks, which represents 98.1% of the assets of the Colombian banking system, **14** banks were eliminated as they do not have complete data for the period analyzed. Table 2 shows the average of some balance sheet data for the banks, according to their size.

The estimation period is from September 2013 to May 2022 with monthly data. Balance sheet variables and the interest rate are in nominal terms, given that inflation is included as an explanatory variable. For

GDP, we use the Monthly Economic Conditions Index (ISE, in Spanish), because GDP growth is published quarterly. Only statistically significant lags are included in the estimation.

Large and medium banks present similar averages for most of the variables in Table 2, besides the important difference in investments over assets, in which medium banks hold the biggest ratio among the three sizes. The funding of big and medium banks come mostly from savings and current accounts, while for small banks, from term deposits. Small banks are the most leveraged and have the highest Tier 1 capital excess.

Table 2. Descriptive statistics of the Colombian banking system (average)

Data*	Size		
	Small	**Medium**	**Big**
Assets (log natural units)	14.81	16.86	18.30
Saving deposits	13.37	32.31	35.61
Checking accounts	2.57	8.98	10.20
Term deposits	38.79	20.40	20.98
Cash and equivalents	8.44	7.11	7.20
Tier 1 (%) excess from 9%	9.55	6.59	5.41
Investments• and derivatives	11.98	25.07	16.61
Liabilities	85.25	90.51	89.63
Leverage (equity/assets)	14.75	9.49	10.37

Source: Financial Superintendence of Colombia. **Note:** Data as of May 2022 and correspond to 14 officially recognized banking entities; other entities were not considered because they were liquidated or are part of mergers during the period from 2013 to 2022. The characterization between small, medium, and large, according to their size, was made based on a ranking by percentiles, 33.3%, 66.6% and 99.9%, respectively. (*) Variables taken as proportion of total assets, except TIER 1. (•) Fixed income and equity positions. Excludes cash and other cash accounts.

4. RESULTS

We report our findings for the BLC in Table 3, the column Model I reports the findings estimated at the mean, while the other columns, the results at various percentiles obtained from the percentile regression. We find that higher interest rates induce lower loan growth, supporting the presence of the BLC along different percentiles. An interesting result is the diminishing effect of the BLC as the percentile increases, implying that the BLC becomes less powerful (except for percentile 80th) as the monetary policy rate reaches its maximums levels. In terms of banks' characteristics, liquidity, size and capitalization are significant.

Table 3. Bank lending channel – total loans results

	Model I	Model II (τ percentile)								
VARIABLES	(Average)	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
$\Delta l_{i,t-1}$	0.998***	0.347***	0.502***	0.641***	0.688***	0.716***	0.727***	0.791***	0.812***	0.839***
	(0.00768)	(0.00321)	(0.00392)	(0.00283)	(0.00342)	(0.00325)	(0.00575)	(0.00402)	(0.00564)	(0.00596)
ΔGDP_t	-0.00761	-0.206***	-0.264***	-0.140***	-0.134***	-0.133***	-0.0958***	-0.0763***	-0.0594***	-0.0455***
	(0.0226)	(0.00369)	(0.0125)	(0.00550)	(0.00523)	(0.00637)	(0.0119)	(0.00684)	(0.00966)	(0.00770)
ΔGDP_{t-1}	0.103***	0.228***	0.155***	0.119***	0.154***	0.166***	0.125***	0.115***	0.110***	0.101***
	(0.0243)	(0.00319)	(0.0114)	(0.00626)	(0.00663)	(0.00785)	(0.0123)	(0.00953)	(0.00737)	(0.00902)
INF_t	-0.398	-0.874***	-0.128	-0.654***	-0.691***	-0.488***	-0.286***	-0.328***	-0.284***	-0.274***
	(0.265)	(0.0960)	(0.0984)	(0.0716)	(0.0716)	(0.0657)	(0.0965)	(0.125)	(0.0944)	(0.105)
INF_{t-1}	0.452	3.082***	0.948***	1.219***	1.150***	0.890***	0.599***	0.557***	0.416***	0.370***
	(0.287)	(0.0855)	(0.0969)	(0.0695)	(0.0730)	(0.0727)	(0.0929)	(0.131)	(0.107)	(0.118)
Allowances_{t-1}	-0.0215***	0.121***	-0.0157***	-0.0199***	-0.0149***	-0.0119***	-0.0182***	-0.0176***	-0.0209***	-0.0229***
	(0.00549)	(0.000624)	(0.00282)	(0.00157)	(0.00194)	(0.00296)	(0.00333)	(0.00256)	(0.00304)	(0.00239)
$\Delta MONPOL_{t-1}$	-1.286**	-7.942***	-3.223***	-2.578***	-2.417***	-1.589***	-1.369**	-0.610**	-1.255**	-0.520
	(0.626)	(0.0452)	(0.326)	(0.534)	(0.407)	(0.322)	(0.576)	(0.280)	(0.579)	(0.711)
dummy_t	0.116	4.070***	-1.343***	-0.825***	-1.159***	-1.137***	-1.103***	-1.003***	-1.136***	-1.044***
	(0.275)	(0.0748)	(0.179)	(0.0776)	(0.121)	(0.128)	(0.159)	(0.0916)	(0.108)	(0.134)
Liq_{t-1}	-0.325**	-1.683***	-0.569***	-0.475***	-0.482***	-0.484***	-0.478***	-0.422***	-0.422***	-0.347***
	(0.156)	(0.0248)	(0.0321)	(0.0190)	(0.0320)	(0.0446)	(0.0449)	(0.0412)	(0.0631)	(0.0469)
$\text{Liq\#MP}_{t-1}$	0.0639*	0.205***	0.0321***	0.0112***	0.0162***	0.0362***	0.0348***	0.0342***	0.0343**	0.0219**
	(0.0335)	(0.00643)	(0.00778)	(0.00357)	(0.00553)	(0.0120)	(0.00967)	(0.0106)	(0.0134)	(0.0102)
Size_{t-1}	-0.00417	-1.394***	0.0727	-0.315**	-0.412***	-0.00211	0.107	0.333***	0.129	0.260
	(0.324)	(0.0233)	(0.103)	(0.159)	(0.123)	(0.0804)	(0.160)	(0.0686)	(0.161)	(0.187)
$\text{Size\#MP}_{t-1}$	-0.0114	0.240***	0.0477***	0.0603**	0.0655***	0.0215	0.0155	-0.0141	0.0242	-0.00879
	(0.0673)	(0.00295)	(0.0183)	(0.0295)	(0.0207)	(0.0160)	(0.0286)	(0.0151)	(0.0297)	(0.0357)
Cap_{t-1}	-0.0357	-2.040***	-1.608***	-1.055***	-0.831***	-0.662***	-0.597***	-0.366***	-0.355***	-0.283***
	(0.0489)	(0.00414)	(0.0263)	(0.0316)	(0.0175)	(0.0314)	(0.0464)	(0.0215)	(0.0359)	(0.0536)
$\text{Cap\#MP}_{t-1}$	0.00816	0.246***	0.214***	0.131***	0.0973***	0.0762***	0.0698***	0.0437***	0.0462***	0.0369***
	(0.0103)	(0.000759)	(0.00524)	(0.00642)	(0.00378)	(0.00580)	(0.00883)	(0.00362)	(0.00580)	(0.00989)
Constant_i	6.303**	35.72***	13.19***	15.87***	16.23***	8.212***	6.273**	0.140	3.873	0.590
	(2.925)	(0.417)	(1.771)	(2.851)	(2.403)	(1.593)	(3.156)	(1.092)	(3.144)	(3.802)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Higher liquidity and capital are related with lower loan growth, and banks with higher liquidity and higher capital present a lower BLC. The effect of the size of banks on credit growth is non-linear among percentiles. For the 10th, 30th and 40th percentiles the effect is negative, while for the 70th is positive, and it is not significant for the other percentiles. Bigger banks show a lower BLC for small percentiles (0.1-0.4). Finally, the dummy variable, which is significant for all percentiles, shows that credit growth was higher during the pandemic than in other periods.[2]

[2] The 10th percentile is the comparison base, and the other percentiles are the marginal effects with respect to this one.

Table 4. Bank lending channel - corporate loans results

VARIABLES	Model I (average)	Model II (τ quantile) 0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
$\Delta l_{i,t-1}$	0.945***	0.532***	0.686***	0.779***	0.807***	0.835***	0.855***	0.845***	0.842***	0.862***
	(0.00956)	(0.00754)	(0.00433)	(0.00348)	(0.000546)	(0.00145)	(0.00103)	(0.00338)	(0.00422)	(0.00497)
ΔGDP_t	-0.148***	-0.270***	-0.204***	-0.168***	-0.174***	-0.180***	-0.184***	-0.172***	-0.172***	-0.161***
	(0.0384)	(0.0453)	(0.0112)	(0.0168)	(0.00576)	(0.0192)	(0.0175)	(0.0146)	(0.0127)	(0.0140)
ΔGDP_{t-1}	0.155***	-0.187	0.185***	0.221***	0.192***	0.217***	0.236***	0.207***	0.193***	0.187***
	(0.0418)	(0.196)	(0.0151)	(0.0245)	(0.0115)	(0.0254)	(0.0177)	(0.0186)	(0.0142)	(0.0167)
INF_t	-0.313	-4.963***	-1.365***	-3.464***	-2.646***	-1.653***	-1.507***	-1.515***	-1.429***	-1.254***
	(0.440)	(0.616)	(0.143)	(0.207)	(0.114)	(0.189)	(0.142)	(0.148)	(0.183)	(0.143)
INF_{t-1}	0.390	1.348**	1.989***	3.461***	2.652***	1.602***	1.275***	1.303***	1.246***	1.083***
	(0.467)	(0.544)	(0.140)	(0.214)	(0.0992)	(0.185)	(0.151)	(0.146)	(0.208)	(0.140)
Allowances_{t-1}	-0.0119	-0.231***	-0.197***	-0.112***	-0.0881***	-0.0771***	-0.0671***	-0.0529***	-0.0501***	-0.0350***
	(0.00734)	(0.00818)	(0.00573)	(0.00135)	(0.000884)	(0.00191)	(0.00178)	(0.00434)	(0.00419)	(0.00497)
$\Delta MONPOL_{t-1}$	1.143	17.11***	-8.227***	-1.445	-0.733***	0.661	1.455**	2.245**	1.317*	4.106**
	(1.399)	(2.057)	(0.660)	(1.194)	(0.192)	(1.142)	(0.701)	(0.939)	(0.698)	(1.669)
$\Delta MONPOL_{t-2}$	-0.997	-22.74***	6.798***	0.0863	-0.359**	-1.009***	-1.750***	-1.648***	-1.338***	-1.231***
	(0.790)	(1.636)	(0.294)	(0.454)	(0.162)	(0.227)	(0.285)	(0.397)	(0.181)	(0.332)
dummy_t	-0.735	-10.28***	-4.503***	-4.206***	-3.742***	-2.685***	-2.465***	-2.556***	-2.711***	-2.585***
	(0.456)	(2.670)	(0.333)	(0.331)	(0.117)	(0.222)	(0.177)	(0.212)	(0.194)	(0.188)
Liq_{t-1}	0.233	1.304***	0.608***	0.397***	0.259***	0.297***	0.286***	0.271***	0.169***	0.288***
	(0.265)	(0.0917)	(0.0419)	(0.0507)	(0.0309)	(0.0934)	(0.0647)	(0.0576)	(0.0609)	(0.0763)
$\text{Liq\#MP}_{t-1}$	-0.0425	0.0865	0.0220*	-0.0197	0.00643	-0.0132	-0.0181	-0.0156	0.00365	-0.0292*
	(0.0560)	(0.0544)	(0.0116)	(0.0163)	(0.00870)	(0.0206)	(0.0149)	(0.0137)	(0.0137)	(0.0173)
Size_{t-1}	-0.00721	4.106***	3.653***	1.986***	1.958***	1.664***	1.427***	1.578***	1.411***	1.987***
	(0.136)	(0.247)	(0.103)	(0.299)	(0.0275)	(0.319)	(0.176)	(0.240)	(0.159)	(0.386)
$\text{Size\#MP}_{t-1}$	-0.00428	0.129	-0.130***	-0.0479	-0.0589***	-0.0613	-0.0383	-0.0864*	-0.0611**	-0.195**
	(0.0320)	(0.0805)	(0.0193)	(0.0565)	(0.00536)	(0.0571)	(0.0321)	(0.0441)	(0.0303)	(0.0789)
Cap_{t-1}	-0.0864	-3.955***	-2.168***	-1.297***	-1.025***	-0.856***	-0.688***	-0.617***	-0.601***	-0.385***
	(0.0980)	(0.112)	(0.0174)	(0.0175)	(0.0102)	(0.0211)	(0.0420)	(0.0553)	(0.0236)	(0.0306)
$\text{Cap\#MP}_{t-1}$	0.0296	0.535***	0.316***	0.187***	0.156***	0.128***	0.0992***	0.0840***	0.0811***	0.0451***
	(0.0216)	(0.0243)	(0.00344)	(0.00387)	(0.00217)	(0.00464)	(0.00878)	(0.0110)	(0.00591)	(0.00621)
Constant_i	-1.428	-45.89***	-52.29***	-26.04***	-26.30***	-23.90***	-20.94***	-23.52***	-19.41***	-32.22***
	(5.155)	(6.578)	(2.130)	(5.365)	(0.615)	(5.821)	(3.574)	(4.978)	(3.166)	(7.169)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Tables 4-6 show the results from equation [1] for the three types of credit: corporate, consumption and mortgage. The BLC for corporate loans is present among some percentiles (10^{th}, 20^{th}, 40^{th}, 50^{th} and 60^{th}; Table 3), while it is not significant for the model at the mean. The diminishing effect of the BLC as the percentile is greater remains for corporate loans, except for the larger percentiles. Banks' characteristics (liquidity, size and capitalization) continue to be significant, but in this case banks with higher liquidity have higher credit growth. As in the total credit regression, banks with higher capital present a smaller BLC, but now liquidity does not affect the BLC and bigger banks have a higher BLC. The dummy variable, as in the case of total loans, is significant for all percentiles, but negative due to the comparison effect versus the base.

Consumer loans show a higher BLC than total and commercial loans (Table 5), although at the mean there is no BLC as in commercial loans. The diminishing effect of the BLC as the percentile increases is also present here, as well as the significancy of banks' characteristics. Banks with higher liquidity and capital have higher credit growth and BLC, while bigger banks present lower credit growth and BLC. The dummy variable is significant for all percentiles and shows that credit growth was higher during the pandemic than in other periods.

Table 5. Bank lending channel - consumer loans results

VARIABLES	Model I (Average)	Model II (τ quantile) 0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
$\Delta l_{i,t-1}$	0.519***	0.0159***	0.0175***	0.0822***	0.566***	0.567***	0.557***	0.549***	0.677***	0.672***
	(0.0692)	(0.000101)	(0.000181)	(0.000417)	(0.000576)	(0.000194)	(0.000153)	(0.000396)	(0.000489)	(0.000350)
ΔGDP_t	0.133	0.116***	0.0716***	0.0537***	0.0458***	0.0360***	0.0334***	0.0325***	0.0130**	0.00849
	(11.98)	(0.00225)	(0.00617)	(0.0122)	(0.00667)	(0.00496)	(0.00845)	(0.00939)	(0.00607)	(0.00722)
ΔGDP_{t-1}	-0.452	-0.0622***	0.0836***	0.116***	0.0842***	0.0850***	0.0883***	0.0718***	0.0690***	0.0693***
	(12.97)	(0.00338)	(0.0109)	(0.0141)	(0.00781)	(0.00748)	(0.0108)	(0.0101)	(0.00755)	(0.00956)
INF_t	7.603	-1.181***	-0.920***	-1.312***	-1.184***	-1.123***	-0.983***	-0.549***	-0.745***	-0.651***
	(138.9)	(0.0797)	(0.135)	(0.114)	(0.0816)	(0.0596)	(0.134)	(0.143)	(0.138)	(0.121)
INF_{t-1}	-6.268	1.856***	0.943***	1.593***	1.431***	1.370***	1.236***	0.940***	1.008***	0.884***
	(145.0)	(0.0768)	(0.134)	(0.140)	(0.0837)	(0.0595)	(0.124)	(0.175)	(0.128)	(0.118)
Allowances_{t-1}	0.602***	0.00318***	0.00121***	0.000602***	0.000539***	0.000111	0.00921***	0.0176***	0.0185***	0.0308***
	(0.108)	(4.70e-05)	(0.000183)	(0.000152)	(0.000156)	(8.39e-05)	(0.000146)	(0.000198)	(0.000212)	(0.000179)
$\Delta MONPOL_{t-1}$	-2.931	-30.32***	-25.63***	-26.77***	-10.28***	-10.47***	-9.290***	-11.13***	-6.463***	-6.056***
	(610.2)	(0.0563)	(0.833)	(0.412)	(0.228)	(0.318)	(0.379)	(0.632)	(0.576)	(0.461)
$\Delta MONPOL_{t-2}$	4.885	3.476***	6.784***	7.638***	4.444***	3.807***	3.611***	4.044***	2.112***	1.733***
	(246.1)	(0.1000)	(0.748)	(0.138)	(0.200)	(0.0727)	(0.226)	(0.291)	(0.154)	(0.155)
dummy_t	-4.286	4.019***	5.916***	5.145***	2.003***	2.115***	1.950***	1.470***	0.870***	0.844***
	(185.2)	(0.0359)	(0.172)	(0.162)	(0.0745)	(0.0605)	(0.128)	(0.177)	(0.160)	(0.113)
Liq_{t-1}	-0.860	1.566***	1.288***	1.095***	0.480***	0.485***	0.518***	0.459***	0.231***	0.231***
	(138.2)	(0.00582)	(0.0223)	(0.0236)	(0.0246)	(0.0247)	(0.0292)	(0.0586)	(0.0597)	(0.0388)
$\text{Liq\#MP}_{t-1}$	-0.118	-0.635***	-0.452***	-0.395***	-0.210***	-0.193***	-0.209***	-0.185***	-0.123***	-0.107***
	(29.19)	(0.00115)	(0.00790)	(0.00681)	(0.00822)	(0.00718)	(0.00934)	(0.0163)	(0.0159)	(0.0102)
Size_{t-1}	0.0129	-4.017***	-2.577***	-2.840***	-0.583***	-0.698***	-0.478***	-0.785***	-0.380***	-0.369***
	(53.52)	(0.0179)	(0.0719)	(0.0905)	(0.0542)	(0.0623)	(0.0480)	(0.120)	(0.118)	(0.0814)
$\text{Size\#MP}_{t-1}$	-0.167	1.909***	1.491***	1.435***	0.500***	0.543***	0.489***	0.546***	0.343***	0.339***
	(12.41)	(0.00215)	(0.0151)	(0.0169)	(0.0132)	(0.0158)	(0.0155)	(0.0221)	(0.0241)	(0.0167)
Cap_{t-1}	-0.307	1.194***	1.438***	1.272***	0.721***	0.707***	0.726***	0.663***	0.474***	0.486***
	(34.37)	(0.00826)	(0.0271)	(0.0210)	(0.0114)	(0.0107)	(0.00851)	(0.0284)	(0.0341)	(0.0155)
$\text{Cap\#MP}_{t-1}$	-0.0529	-0.184***	-0.237***	-0.198***	-0.119***	-0.113***	-0.112***	-0.102***	-0.0728***	-0.0774***
	(7.261)	(0.00147)	(0.00498)	(0.00433)	(0.00273)	(0.00225)	(0.00188)	(0.00535)	(0.00685)	(0.00328)
Constant_i	18.45	38.06***	9.689***	18.84***	-4.380***	-2.429**	-6.328***	0.544	-1.736	-1.852
	(2,612)	(0.416)	(1.309)	(1.692)	(1.037)	(1.162)	(0.855)	(2.360)	(2.738)	(1.719)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Housing loans support the presence of the BLC, with a diminishing effect as the percentile increases except for the larger percentiles (Table 6). In the case of the mean model there is no BLC as in commercial and consumer loans. Banks' characteristics continue to be significant in the quantile regression. As in consumer loans, banks with higher liquidity and capital have higher credit growth and BLC, while bigger banks present lower credit growth and BLC. Finally, the dummy variable is significant for all percentiles and shows that credit growth was higher during the pandemic than in other periods.

Table 6. Bank lending channel - housing loans results

VARIABLES	Model I (Average)	Model II (τ percentile) 0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
$\Delta l_{i,t-1}$	0.687***	0.00391***	0.00319***	0.00287***	0.00257***	0.0333***	0.0308***	0.146***	0.341***	0.344***
	(0.0254)	(1.61e-06)	(3.20e-06)	(1.46e-06)	(8.67e-06)	(3.62e-06)	(1.55e-06)	(5.10e-06)	(6.85e-06)	(1.86e-05)
GDP_t	0.130	0.182***	0.191***	0.221***	0.181***	0.132***	0.132***	0.110***	0.0709***	0.0592***
	(3.270)	(0.0307)	(0.0206)	(0.00410)	(0.0143)	(0.0138)	(0.0221)	(0.0201)	(0.0176)	(0.0171)
GDP_{t-1}	-0.273	-0.309***	-0.249***	-0.143***	-0.220***	-0.202***	-0.149***	-0.102***	-0.079***	-0.065***
	(3.485)	(0.0277)	(0.0244)	(0.00266)	(0.0157)	(0.0135)	(0.0214)	(0.0249)	(0.0189)	(0.0139)
INF_t	11.68	10.15***	7.603***	5.977***	6.726***	6.673***	5.539***	4.170***	3.521***	3.244***
	(34.24)	(0.253)	(0.442)	(0.0412)	(0.252)	(0.221)	(0.240)	(0.317)	(0.234)	(0.212)
INF_{t-1}	-12.11	-11.61***	-8.458***	-5.781***	-6.570***	-6.865***	-5.315***	-3.977***	-3.120***	-2.724***
	(35.36)	(0.319)	(0.442)	(0.0419)	(0.247)	(0.171)	(0.244)	(0.309)	(0.249)	(0.210)
$Allowances_{,-1}$	-0.000676	-0.000169***	-0.000138***	-0.000125***	-0.000112***	-0.00147***	-0.00135***	-0.00642***	-0.0150***	-0.0152***
	(0.000776)	(6.90e-08)	(1.55e-07)	(5.85e-08)	(3.75e-07)	(1.46e-07)	(6.24e-08)	(1.96e-07)	(2.71e-07)	(8.04e-07)
$\Delta MONPOL_{t-1}$	5.261	-26.39***	-39.31***	-32.57***	-38.94***	-44.35***	-41.61***	-36.77***	-25.70***	-24.41***
	(133.6)	(0.329)	(1.781)	(0.0998)	(0.770)	(0.608)	(0.651)	(1.094)	(1.302)	(1.354)
$\Delta MONPOL_{t-2}$	8.676	9.596***	9.054***	6.811***	4.223***	3.211***	2.342***	2.140***	1.797***	0.948***
	(51.21)	(0.114)	(0.666)	(0.0880)	(0.549)	(0.467)	(0.289)	(0.465)	(0.427)	(0.337)
dummy,	-11.17	-9.121***	5.687***	6.082***	7.455***	8.501***	8.360***	6.902***	4.833***	5.304***
	(49.96)	(0.112)	(0.540)	(0.0729)	(0.197)	(0.185)	(0.233)	(0.333)	(0.186)	(0.376)
Liq_{t-1}	3.611	1.572***	2.231***	2.929***	1.831***	0.352***	0.566***	0.447***	0.372***	0.0459
	(36.53)	(0.0374)	(0.129)	(0.0271)	(0.0896)	(0.0703)	(0.0933)	(0.0807)	(0.0595)	(0.128)
$\text{Liq}_{t-1}\#\text{MP}_{t-1}$	-0.542	-0.787***	-1.010***	-1.000***	-0.874***	-0.516***	-0.463***	-0.423***	-0.337***	-0.198***
	(7.387)	(0.0120)	(0.0490)	(0.00881)	(0.0285)	(0.0151)	(0.0206)	(0.0205)	(0.0150)	(0.0277)
Size_{t-1}	0.640	4.198***	-1.667***	0.848***	-3.029***	-6.163***	-5.810***	-5.365***	-3.583***	-3.854***
	(13.40)	(0.0594)	(0.315)	(0.0507)	(0.143)	(0.0888)	(0.195)	(0.269)	(0.346)	(0.424)
$\text{Size}_{t-1}\#\text{MP}_{t-1}$	-0.198	2.122***	2.884***	2.401***	2.879***	3.219***	3.022***	2.661***	1.851***	1.718***
	(2.334)	(0.0151)	(0.0898)	(0.0119)	(0.0300)	(0.0154)	(0.0439)	(0.0527)	(0.0640)	(0.0842)
Cap_{t-1}	4.726	3.628***	3.054***	1.900***	2.502***	3.342***	3.117***	2.792***	2.090***	1.907***
	(10.76)	(0.0260)	(0.0627)	(0.0115)	(0.0364)	(0.0313)	(0.0473)	(0.0529)	(0.0695)	(0.0537)
$\text{Cap}_{t-1}\#\text{MP}_{t-1}$	-0.380	-1.586***	-1.246***	-0.817***	-0.780***	-0.868***	-0.783***	-0.691***	-0.482***	-0.383***
	(2.179)	(0.00738)	(0.0166)	(0.00257)	(0.0112)	(0.00601)	(0.0116)	(0.0197)	(0.0135)	(0.0147)
Constant_i	-99.47	-124.5***	-28.85***	-68.35***	-0.106	53.36***	48.78***	48.43***	28.77***	37.04***
	(625.4)	(1.119)	(5.273)	(0.716)	(2.314)	(1.642)	(3.625)	(4.553)	(5.581)	(7.404)

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. CONCLUSIONS

We find evidence of the BLC in Colombia through our unconditioned quantile regressions, for total credit and for each type of credit (commercial, consumer and housing), while average models only support the BLC for total loans. In general, in the quantile regression the BLC decreases as the percentile increases, which means that the level of the policy rate is relevant to the incidence of the BLC and the size of the pass through.

We also confirmed several facts of the literature, the characteristics of the balance sheet of credit institutions, are relevant to explain the BLC in Colombia. For total and commercial loans, less capitalized and less liquid banks face a higher BLC, while for size the ratio is nonlinear for total loans and for commercial loans larger banks show a higher BLC. For consumer and housing loans, banks with higher capitalization and liquidity have a higher BLC, and for commercial loans, larger banks show a higher BLC.

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