Credit Cycles, Credit Risk and Countercyclical Loan Provisions

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Abstract

In this paper we investigate the impact of rapid credit growth on ex ante credit risk. We present micro-econometric evidence of the positive relationship between rapid credit growth and deterioration in lending portfolios: Loans granted during boom periods have higher probability of default than those granted during periods of slow credit growth. In addition, given their importance for macroprudential policy, we evaluate the effectiveness of the implementation of the countercyclical loan provisions. We find a negative relationship between the amplitude of credit cycles and this kind of macroprudential tool.

Keywords: Ex ante credit risk, credit cycles, countercyclical provisioning.
JEL E32, E51, E60, G18, G21.

1 Introduction

Deep credit cycles are frequently symptoms of macroeconomic turbulence. These come hand-in-hand with swings in asset prices and strong movements in investment

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and output. From the point of view of financial stability these are also associated with financial fragility. Credit booms are reinforced and reinforce the business cycle according with the theory developed by Bernanke et al. (1999), and Kiyotaki and Moore (1997). According to this approach, economic agent's net worth is affected by movement in asset prices (driven by expectations of higher dividends) giving place to improvements in collateral. This increase in collateral allows firms and households to access credit. In turn, the rise in credit finances investment and consumption which further rise output and asset prices. The multiplier effect exacerbates the initial increase in credit, investment, asset prices and output. This mechanism is even more important in the case of asset price bubbles because when the bubble bursts loan losses are important and may cause an economic downturn. This mechanism is known in the literature as the financial accelerator mechanism and empirical evidence about it has been presented by Christensen and Dib (2008) for the United States and Lï¿œpez et al. (2009) for Colombia.

In more recent theoretical developments about the Great Recession in the late 2000s, authors such as Aikman et al. (2010) who build on early work by Rajan (1994) explain how the increased competition among banks, originated in the deregulation of the US banking sector in the 1970s and 1980s, resulted in a financial system where banks were increasingly required to keep pace with the returns on equity offered by their rivals leading to increased risk taking.

In Rajan (1994)'s model, bank management is rational but have short term concerns. In addition to maximizing the bank's earnings, it is concerned with its reputation, i.e. labor market's perception of its abilities. In this model, the market does not observe the bank loan portfolios but its earnings. Consequently, the bank tries to manipulate its current earnings by altering its credit policy using more liberal credit policies that boost current earnings at the expenses of future earnings. A case of competitive coordination failure originated in this kind of behavior of banks is presented by Aikman et al. (2010) who reports that during 1992-2003, major UK, US and European banks reported high and synchronized returns. But they did so at the expense of higher risk in aggregate. In a dynamic setting, "When there is only a small probability of an adverse shock to the borrowing sector, banks are forced to maintain excessively liberal credit policies. This in turn leads to overinvestment by the borrowing sector which increases the likelihood of an adverse shock to it. It is only after the condition of the borrowing sector deteriorates considerably that banks have an incentive to tighten the supply of credit. When they retrench, investment is suddently curtail, the excesses are drained out of the borrowing sector and the cycle resumes" Rajan (1994).

All and all, it is clear that the increasing attention among scholars and policy makers about regulation, competition and risk taking is justified. Some of the responses have addressed the relevance of using macroprudential tools to rein in credit excesses. For example, Jimï¿œnez et al. (2012) point out that some tools like countercyclical capital buffers help, first, to mitigate credit crunches because the increase in provisioning requirements in booms provide additional buffers in downturns. And second, higher requirements on bank own funds can cool credit-led booms, either because banks internalize more of the potential social costs of credit defaults (through a reduction in moral hazard) or charge a higher loan rate due to the higher cost of bank capital (see Holmstrom and Tirole (1997); Morrison and White (2004); Adrian and Song Shin (2010) and Shleifer and Vishny (2010)).

In the case of Colombia, the banking supervisory authority (Superfinanciera) introduced a countercyclical component to banks' individual provisions since July 2007. This component is accrued in an additional form for each borrower with the goal of accumulate provisions that will be used later on by each bank in moments of deterioration of the lending activity.

In this paper, first, we present micro-econometric evidence of the positive relationship between rapid credit growth and deterioration in lending portfolios in Colombia. We find empirical evidence of a positive relationship between credit cycles and ex ante credit risk: Loans granted during boom periods have higher probability of default than those granted during periods of slow credit growth. In this sense, this paper constitutes the first study based on loan-to-loan information for Colombia.

Second, given their importance for macroprudential policy, we evaluate the effectiveness of the implementation of the countercyclical loan provisions in Colombia in terms of smoothing the credit cycle and the risk taking behavior of banks. To draw inferences about the causal effects of treatments, (i.e. interventions) in this case the countercyclical provisions, we need a homogeneous database that allows us to have the "history" of a loan during the period of the intervention and before the intervention. We implement a matching technique that allows us to have this homogeneous database to be used later on in our econometric analysis. Our findings are that these kinds of provisions have had the effect of dampening the credit cycle in Colombia.

2 Credit Growth and Credit Risk

We focus in an individual loan level analysis to draw conclusion regarding the relationship between rapid credit growth and credit risk. We test if those loans granted during credit booms are riskier than those granted when the bank is reining in loan growth. This analysis would provide empirical microfoundations for prudential regulatory tools in policies regarding rapid credit growth.

The database we use in our study is recorded by banks and reported to the Superfinanciera, which is the supervisor in Colombia of the banking system. The database consists of over two million commercial loans whose amount represents near 70 percent of the total amount of loans granted by banks in Colombia. We focus on new loans granted to non financial firms with maturity larger than one year and keep track of them the following years. The period analyzed covers 2003.1-2011.2. Following Saurina and Jimenez (2006), the equation to be estimated relates the probability of default at an individual loan level and its relation to the cyclical position of the bank credit policy:

$$\begin{aligned} Pr(DEFAULT_{blt+k}=1) \quad = \quad & F(\theta+\alpha(LOANG_{bt}-averageLOANG_b)+\beta \mid LOANG_{bt}- \\ & averageLOANG_b \mid +\chi LOANCHAR_{lt}+\delta_1 BANKCHAR_{bt}+ \\ & \delta_2 BORROWERCHAR_{ft}+\varphi_t+\eta_i \end{aligned} \quad (1)$$

where the probability of default of loan l, in bank b, some k years after being granted (i.e., at $t+2$, $t+3$, and $t+4$)[1]is a logistic function of the characteristics of the loan, $LOANCHAR$, such as the amount of the loan, LN(SIZE OF THE LOAN), collateral (COLLATERAL) and maturity of the loans using dummies for 1 to 3 years

[1] Following Saurina and Jimenez (2006), we consider that a loan is in default when its doubtful part is larger than 5 percent of its total assets. The doubtful part of of the loan is calculated based on information recorded in the form 341. It corresponds to PI*EA*PDI, where PI is the non-payment probability, EA is the asset exposure at the time of no payment and PDI is the loss given no payment.

and 3 and more years, benchmark being short-term loans (from 0 to 1 year). We also control for bank characteristics, $BANKCHAR$, which include SIZE (each bank total assets/ bank system total assets), OWN FUNDS/TOTAL ASSETS (the amount of bank equity over total assets), a measure of risk appetite measured by BANK NPLb-NPL (the difference between the bank and banking system non-performing loans) and INTERBANK POSITION (which is bank net interbank lending). Other valuable feature of our database is that it allows us to include not only loan characteristics but also borrower characteristics, $BORROWERCHAR$, that help to disentangle supply and demand effects as the composition of the pool of borrowers and loans may change over time. The variable LN (1+NUMBER OF BANK RELATIONSHIPS) allows us to identify the number of bank connections of each borrower. The variable LN(2+AGE AS BORROWER) measures the age of the borrower in the financial system and the variable BORROWER RISK measures if the borrower was overdue six months before it was granted another loan. We also control for macroeconomic characteristics φ_i such as GDP growth and the interest rate. Finally, we control for the great heterogeneity due to firm effects η_i.

Once we have controlled for bank, borrower, loan and macroeconomic characteristics, we analyze the impact on the probability of default of relative loan growth of each bank at time t with respect to financial loans granted to non financial firms $(LOANG_{bt} - averageLOANG_b)$, that is the current lending position of each bank in comparison to its average loan growth. If the coefficient α is positive it means that during booms the credit risk increases. This could be related to low credit standards during booms. On the contrary, when the credit growth is below average, banks becomes much more careful in scrutinizing loan applications; as a result, next year defaults decrease significantly. In this sense, it is important to test for the asymmetries in this relationship in each phase of the credit cycle. In order to eliminate outliers, we have considered only those banks with a loan growth rate within the 5th and 95th percentile.

The definitions and descriptive statistics of the dependent and independent variables are presented in Table 1. As it can be observed in the table, the percentage of loans in default in the second year is about 20 percent. For the following years, three and four, this percentage is very similar. The measure for interest rate is the deviation of the policy interest rate from the natural rate (to avoid endogeneity problem) and its mean value was around 0.29 percent. The average size of the banks is 6.85 percent with a large standard deviation. In this sense, it is worth noting that in Colombia 5 out of 30 banks own near 60 percent of total assets in the banking system. The mean banks' equity to total assets ratio is 5.21 percent with a maximum of 14.88 percent. In average, the non-performing loans of the banks were lower than the total system non-performing loans in about 3.95 percent. With respect to borrower characteristics, 4.9 percent of borrowers were risky in the sense that they were overdue six months before having access to another loan. In average, borrowers had a history in the banking system of 2.3 years. With respect to loans characteristics, near 50 percent of loans had collateral and loans' terms were concentrated in longer maturities, between 3 and 5 years. Finally, the average GDP growth was 4.4 percent.

Tables 2 through 4 present the results. Each table corresponds to defaults two, three and four years later. The first row in column 1 in the tables corresponds to our variable of interest. The coefficient α is positive and significant. This means that when loan growth of the bank is above average, the likelihood to default on loans increases in the following years. The result is robust when we consider defaults three and four years after the loan is granted.

We also analyze if there is an asymmetric effect of loan growth on risk (columns 2, 4 and 6 in tables 2, 3 and 4). The test of asymmetry of the credit cycle indicates that the probability of default is not affected differently during booms that during bad times. Both, in good times and in bad times, we find a positive and significant impact on future defaults (two and four years later). This result is in opposite direction with findings by Saurina and Jimenez (2006) for the case of Spain.

With respect to the control variables some of the results are in line with other studies. Probability of default increases with lower GDP growth. This result reinforces the notion that there is, embedded in the behavior of banks, a mechanism that changes their perception of risk in response to macroeconomic conditions. A higher rate of growth of the economy increases the probability of default of new loans and lowers the one of outstanding loans. High levels of economic growth negatively impact the perception of risk of outstanding loans and reduce their probabilities of default through, among other things, cash flow implications. By the same token, as the interest rate increases the probability of default on outstanding loans also rises.

As regards to loan specific characteristics, we find that smaller and short-term loans are more risky, which coincides with what can be expected in a credit market with asymmetric information and economies of scale in the lending activity. If the loan has collateral, the probability of future defaults decreases. This result could be due to the fact that as lending standards increase the probability of default decreases. As for bank characteristics, the impact on future defaults of bank size and bank leverage seem counter intuitive. Nonetheless the relationship between banks' non-performing loans and the likelihood to default on loans is positive.

Borrowers' characteristics also have the expected signs and they are in line with findings in the literature of risk taking. If the borrower was in default six months before it was granted another loan, the likelihood to default on loans increases in the following years. This result also confirms that there is persistence in the credit market that is enhanced by the behavior of banks, probably derived from higher interest rates that are charged on loans to "bad" borrowers. If the borrower has a long history in the banking system the probability of future defaults is lower. And finally a borrower with more bank interconnections has a higher likelihood to default on loans.

In order to establish the economic relevance of the results we compute the semielasticity of the credit growth by estimating the model when the loan growth rate is introduced without any comparison to its average value. The results are presented in Table 5. As can be observed from the table, the results are robust for the second and third year. The semi-elasticity of the credit growth is 0.73 percent for default in $t+2$[2] which means that the if a bank grows 1 percentage point, then the likelihood of default in $t+2$ is increased by 0.73 percent. Thus the economic impact is important.

3 Effectiveness of countercyclical provisions in Colombia

In this section we describe the main characteristics of the countercyclical provisions introduced in Colombia in order to evaluate their performance in terms of dampening the credit growth and the risk taking behavior of banks.

[2] The marginal effect of the k-variable is computed as $ME_k = \frac{d\left[Prob(y=1|\bar{x}\right]}{dx_k} = \Lambda(\hat{\beta}\bar{x})\left[1-\Lambda(\hat{\beta}\bar{x})\right]\hat{\beta}_k$. The semi-elasticity is given by $ME_k/Average\,Default$.

3.1 Countercyclical loan provisions as macroprudential tool.

Rapid credit growth usually come hand-in-hand with deterioration of quality standards and subsequent financial crisis. Moreover, credit booms in emerging economies are often associated with macroeconomic turbulence: About 68 percent of the credit booms in emerging economies are associated with currency crises, 55 percent with banking crises, and 32 percent with sudden stops, Mendoza and Terrones (2008). In industrial economies, the recent financial crises have been the worst since the Great Depression. This has brought the attention of policymakers and regulators that are searching for macroprudential policies that help to prevent financial crises.

As pointed out by Jimï¿œnez et al. (2012): "Among macroprudential instruments, the ones that have attracted most interest are countercyclical tools. G20 meetings have stressed the importance of mitigating the procyclicality of the financial system. . . The intuition for a countercyclical capital tool is that banks should increase their capital in good times and deplete them in bad times. A higher level of requirements in expansions should contribute to moderate lending. A lowering of capital requirements in bad times should reduce the incentives of banks to cut additionally their lending and, therefore, to worsen the recession. This is precisely the macro dimension of a regulatory tool (capital requirements in this example) or, in short, a macroprudential tool."

In the particular case of the Colombian economy, credit cycles have been deep in the last couple of decades. Concerned about financial stability issues, the Superfinanciera (the financial supervisor of the banking system) introduced a countercyclical component to the individual provisions since July 2007. This component corresponds to the part of individual provision that is accrued in an additional form for each borrower during good times with the goal of accumulating provisions that later on will be used by each bank in moments of deterioration of the lending activity.

The amount of this component depends on the particular situation of each bank. When the bank is financially robust and the quality of its lending portfolio is good, it must accumulate countercyclical provisions and in opposite times, it can release part of its buffer. Each financial institution must accumulate or deplete its countercyclical provisions according to four criteria: Quality, efficiency, fragility and loan growth. A more detailed description of the methodology is provided in appendix A.

The buffer build up accordingly is countercyclical because the required provisioning in good times is over and above specific average loan loss provisions, and in bad times there is a release of the buffer that helps to cover specific provisions needs to ameliorate the pressure on the supply of credit.

3.2 Data and identification strategy

For this part of our study we also study the records on the granted business loans reported by the Superfinanciera which contains confidential and very detailed information at the loan level on all loans granted by banks. As it was mentioned in the previous section, the database contains over two million commercial loans whose amount corresponds to approximately 70 percent of total lending.

Regarding identification, a challenge when testing the impact of loan provisions on loan growth is separate supply from demand. Our identification strategy is facilitated by the fact that in Colombia the financial system is bank dominated, the credit to GDP ratio is near 55 per cent and most banks do not have access to bond financing. In this sense we do not have to isolate the so called "bank lending channel" as in Gambacorta and Mistrulli (2004). In some studies the analysts have used different identification approaches but most of them with bank level data. Some have used the cross-country nature of banking to identify the supply of credit where demand is presumably not affected by a shock in another country (see for example Mora and Logan (2012)). Others like Gambacorta and Mistrulli (2004) use vector autoregressions in which proxies for demand are included directly. Others have used a matched bank approach (see Carlson et al. (2011)). To our knowledge, the only study that identifies the supply of credit to a firm level data is the one by Jimï¿œnez et al. (2012).

In our case, the availability of a firm-level database provided by the Superfinanciera offers an ideal experimental setting for identification. Given that the introduction of countercyclical provisions have bank-specific effects that differ according to banks' lending portfolio, the shock cannot be considered "random" (we need that causes banks' provisions to be differentially affected is uncorrelated with the impact of provisions on banks' growth in lending). Following Jimï¿œnez et al. (2012), in loan-level regressions, when we analyze credit availability, we saturate with firm or firm-time fixed effects to capture both observed and unobserved time-varying heterogeneity in firm fundamentals (i.e., it captures credit demand and characteristics of the bank's portfolio composition), while controlling exhaustively for other bank and loan characteristics. According to the availability of data, our firm fixed effects variables are borrower's age, borrower's risk and borrower's bank interconnections.

3.3 Empirical Strategy and Results

Our goal in this section is to assess the causal effect of countercyclical provisions by means of a counterfactual model (see appendix B). In this model, we use the set of characteristics [3]of the loans that were granted after the intervention, July 2007, and use them to obtain a set of loans granted before the intervention with "exactly" the same characteristics. This is done by computing a propensity score for each loan. In a random database, for the period 2003.1-2011.2, the propensity score will give us the probability that a loan will be assigned to a control group (group without countercyclical provisions) or to a treatment group (group with countercyclical provisions).

Then, using the propensity score, we match the loans in the control group with those in the treatment group. The resulting matched credits make up a set that reflects a synthetic situation in which there is a loan market of exactly the same characteristics before and after 2007. At this stage, we are able to assess the causal effect of the countercyclical provisions on loan growth using as econometric specification the equation:

$$LLoanA_{q,l,t} = \alpha + \beta * Treatment + Characteristics_{q,l,t} + e_{q,l,t} \qquad (2)$$

where $LLoanA_{q,l,t}$ is the natural log of the amount of the loan in the q-percentile; $Treat$ indicates if the credit was granted during the period 2007.3 and 2011.2; $Characteristics_{q,l,t}$ is a vector of interactions and $e_{q,l,t}$ is the error term.

In Table 6 we present the results for the counterfactual distribution. In the top of the table we observe that the estimated coefficient for the parameter β goes from -10.91 percent for the smaller loans to -8.18 percent for the biggest loans. These

[3] We use an exogenous set of variables that correspond to bank characteristics (size, leverage, liquidity, relative non-performing loans positions), loan characteristics (amount, maturity and collateral), borrower characteristics (borrower risk, age as borrower) and some macroeconomic variables (GDP growth and deviation of real interest rate from the natural level).

estimates imply that the intervention cuts the amount of the loans in a sizable way. These results are robust under different specifications of the model.

4 Conclusions

Using an individual loan level analysis for the Colombian economy, this study shows that during credit booms the likelihood to defaults on loans increases during following years and when credit growth is below average, banks become much more careful in scrutinizing applications which decreases future defaults. This is evidence that in Colombia, like other economies, when competition increases banks alter their credit policies in order to report high earnings relative to those of their rivals. This gives rise to a coordination failure, as banks collectively risk-up. That, in turn, generates a systematic credit boom and subsequent bust when risk is realised, Aikman et al. (2010).

This evidence about the pro-cyclical relationship between rapid credit growth and ex ante credit risk is an argument that favors the Superfinanciera's decision of introducing countercyclical provisions in July 2007. These provisions act as a buffer that allow financial institutions to accumulate extra provisions when the institution is financially robust and release them in bad times. Moreover, our results about the effect of the countercyclical provisions on credit growth in Colombia show that these have contributed to dampen the credit cycle. This in turn, indirectly (by reining in credit excesses) lowers ex ante credit risk. In addition, the monetary policy authority would not have to rely so strongly in the only instrument that has to stabilize the price level, the interest rate.

References

Adrian, T. and Song Shin, H. (2010). Financial intermediaries and monetary economics. In Friedman, B. M. and Woodford, M., editors, *Handbook of Monetary Economics*, volume 3 of *Handbook of Monetary Economics*, chapter 12, pages 601–650. Elsevier.

Aikman, D., Haldene, A. G., and Nelson, B. (2010). Curbing the credit cycle. *8th Annual Conference: Microfoundations for Modern Macroeconomics*.

Altunbas, Y., Gambacorta, L., and Marques-Ibanez, D. (2010). Bank risk and monetary policy. *Journal of Financial Stability*, 6(3):121–129.

Amador, J., Gï¿œmez-Gonzï¿œlez, J., and Pabï¿œn, A. (2013). Loan growth and bank risk: new evidence. *Financial Markets and Portfolio Management*, 27(4):365–379.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. In Taylor, J. B. and Woodford, M., editors, *Handbook of Macroeconomics*, volume 1 of *Handbook of Macroeconomics*, chapter 21, pages 1341–1393. Elsevier.

Borio, C. and Zhu, H. (2008). Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism? BIS Working Papers 268, Bank for International Settlements.

Carlson, M., Shan, H., and Warusawitharana, M. (2011). Capital ratios and bank lending: a matched bank approach. Technical report.

Christensen, I. and Dib, A. (2008). The financial accelerator in an estimated new keynesian model. *Review of Economic Dynamics*, 11(1):155–178.

Delis, M. D. and Kouretas, G. P. (2011). Interest rates and bank risk-taking. *Journal of Banking & Finance*, 35(4):840–855.

Disyatat, P. (2011). The bank lending channel revisited. *Journal of Money, Credit and Banking*, 43(4):711–734.

Foos, D., Weber, M., and Norden, L. (2009). Loan growth and riskiness of banks. *Banking and Finance*, 34:2929–2940.

Gambacorta, L. (2009). Monetary policy and the risk-taking channel. *BIS Quarterly Review*.

Gambacorta, L. and Mistrulli, P. E. (2004). Does bank capital affect lending behavior? *Journal of Financial Intermediation*, 13(4):436–457.

Holmstrom, B. and Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *The Quarterly Journal of Economics*, 112(3):663–91.

Jimï¿œnez, G., Ongena, S., Peydrï¿œ, J.-L., and Saurina, J. (2012). Macroprudential policy, countercyclical bank capital buffers and credit supply: Evidence from the spanish dynamic provisioning experiments. Working Papers 628, Barcelona Graduate School of Economics.

Jimï¿œnez, G., Ongena, S., Peydrï¿œ-Alcalde, J. L., and Saurina, J. (2007). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk? CEPR Discussion Papers 6514, C.E.P.R. Discussion Papers.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105(2):211–48.

Lï¿œpez, M., Prada, J. D., and Rodrï¿œguez, N. (2009). Evidence for a financial accelerator in a small open economy,and implications for monetary policy. *ENSAYOS SOBRE POLï¿œTICA ECONï¿œMICA*.

Lï¿œpez, M., Tenjo, F., and Zï¿œrate, H. (2012). The risk-taking channel in colombia revisited. *ENSAYOS SOBRE POLï¿œTICA ECONï¿œMICA*.

Mendoza, E. G. and Terrones, M. E. (2008). An anatomy of credit booms: Evidence from macro aggregates and micro data. NBER Working Papers 14049, National Bureau of Economic Research, Inc.

Mora, N. and Logan, A. (2012). Shocks to bank capital: evidence from uk banks at home and away. *Applied Economics*, 44(9):1103–1119.

Morrison, A. and White, L. (2004). Crises and capital requirements in banking. CEPR Discussion Papers 4364, C.E.P.R. Discussion Papers.

Rajan, R. G. (1994). Why bank credit policies fluctuate: A theory and some evidence. *The Quarterly Journal of Economics*, 109(2):399–441.

Saurina, J. and Jimenez, G. (2006). Credit cycles, credit risk, and prudential regulation. MPRA Paper 718, University Library of Munich, Germany.

Shleifer, A. and Vishny, R. W. (2010). Asset fire sales and credit easing. *American Economic Review*, 100(2):46–50.

List of Tables

Tab. 1: Descriptive Statistics

Variables	Definition	Mean	Std.Dev	Min	Max
Default	We consider that a loan is in default when its doubtful part is larger than 5 percent of its total assets (at k=2)	20.37	-	-	-
INTEREST RATE (%)	Deviation of short-term interest rate from natural rate	0.29	1.21	-1.30	2.91
BANK SIZEb (%)	Relative size of the bank vis-a vis the other banks	6.85	4.69	0.17	20.67
OWN FUNDS/TOTAL ASSETS$_b$ (%)	The amount of bank equity over total bank assets	5.21	4.19	0.09	14.88
INTERBANK POSITION/TOTAL ASSETS$_b$(%)	The net amount of interbank lending by the bank over total assets	-0.63	2.72	-26.57	9.73
BANK NPLB-NPL(%)	The difference between the bank and the other banks level of NPLs	-3.95	24.03	-87.31	86.72
BORROWER RISK$_f$ (0/1)	1 if the borrower was overdue any time before on another loan	4.90	21.59	0.00	100.00
LN(2+AGE AS BORROWER$_f$)	Age is the number of years from the first time the firm borrowed from a bank	2.64	0.65	-0.03	5.34
LN(SIZE OF THE LOAN$_l$)	The log of the loan amount	15.13	1.28	0.00	20.41
MATURITY 0m-1y (0/1)	1 if the loan matures between before 1 year	0.14	0.34	0.00	1.00
MATURITY 1y-2y (0/1)	1 if the loan matures between 1 year and 2 years	0.05	0.22	0.00	1.00
MATURITY 2y-3y (0/1)	1 if the loan matures between 2 year and 3 years	0.13	0.33	0.00	1.00
MATURITY 3y-4y (0/1)	1 if the loan matures between 3 year and 4 years	0.35	0.48	0.00	1.00
MATURITY 4y-5y (0/1)	1 if the loan matures between 4 year and 5 years	0.09	0.29	0.00	1.00
MATURITY 5y-High (0/1)	1 if the loan matures after 5 years	0.24	0.43	0.00	1.00
GDPG(%)	Growth in real gross domestic product	4.40	2.02	0.87	7.67
EFFICIENCY RATIO (%)	Operating Margin/Total Assets	0.49	0.34	-0.97	0.99
FINANCIAL INCOME/ATA(%)	Interest income plus dividends received over average total assets	2.53	0.29	1.99	3.13

Tab. 2: Estimations Results of Equation (1): Part A.

Variables	(1)		(2)	
	Coeff.	**Sig.**	**Coeff.**	**Sig.**
Dependent Variable	$DEFAULT_{ijt+2}$ *(0/1)*		$DEFAULT_{ijt+2}$ *(0/1)*	
LOANG_{bt}-AVERAGE $\text{LOANG}_b(\alpha)$	0.00012	***	-0.00014	***
$\lvert LOANG_{bt} - AVERAGELOANG_b \rvert(\beta)$	-	-	0.00040	***
BANK $\text{SIZE}_{b,t}$	0.23757	***	0.26126	***
OWN FOUNDS/TOTAL $\text{ASSETS}_{b,t}$	4.92541	***	4.84037	***
$\text{NPL}_{b,t}$-NPL_t	0.17542	***	0.16914	***
BORROWER $\text{RISK}_{f,t}$	1.99213	***	1.99146	***
LN(2+AGE AS $\text{BORROWER})_{f,t}$	-0.04336	***	-0.04351	***
LN(1+NUMBER OF BANK $\text{RELATIONSHIPS})_{f,t}$	0.19450	***	0.19597	***
$\text{COLLATERAL}_{l,t}$ (0/1)	-0.55900	***	-0.55724	***
LN(SIZE OF THE $\text{LOAN}_{l,t}$)	-0.06496	***	-0.06519	***
MATURITY_l 1Y-3Y (0/1)	0.01435	***	0.01381	***
MATURITY_l 3Y-MORE (0/1)	-0.34199	***	-0.34087	***
INTEREST RATE_t	0.05983	***	0.06053	***
GDPG_t	-1.99237	***	-1.97802	***
T	0.00704	***	0.00703	***
-LOGLIKELIHOOD	-152644.2049	***	-152632.8964	***
CONSTANT	-0.188954438	***	-0.213215756	***
Test Asymmetric Impact				
(p-value)				
$\alpha + \beta = 0$	-		$<$.0001	
$\alpha - \beta = 0$	-		0.0004	

Tab. 3: Estimations Results of Equation (1): Part B.

Variables	**(3)**		**(4)**	
	Coeff.	**Sig.**	**Coeff.**	**Sig.**
Dependent Variable	$DEFAULT_{ijt+3}$ *(0/1)*		$DEFAULT_{ijt+3}$ *(0/1)*	
LOANG$_{bt}$-AVERAGE LOANG$_b(\alpha)$	0.00016	***	0.00021	***
$\|LOANG_{bt} - AVERAGELOANG_b\|(\beta)$	-	-	-0.00006	***
BANK SIZE$_{b,t}$	0.64153	***	0.64923	***
OWN FOUNDS/TOTAL ASSETS$_{b,t}$	2.50416	***	2.45405	***
NPL$_{b,t}$-NPL$_t$	-0.16485	***	-0.16150	***
BORROWER RISK$_{f,t}$	2.08732	***	2.10175	***
LN(2+AGE AS BORROWER)$_{f,t}$	-0.03206	***	-0.03321	***
LN(1+NUMBER OF BANK RELATIONSHIPS)$_{f,t}$	0.17973	***	0.18186	***
COLLATERAL$_{l,t}$ (0/1)	-0.51065	***	-0.51543	***
LN(SIZE OF THE LOAN$_{l,t}$)	-0.08491	***	-0.08501	***
MATURITY$_l$ 1Y-3Y (0/1)	0.25552	***	0.25416	***
MATURITY$_l$ 3Y-MORE (0/1)	-0.28924	***	-0.28478	***
INTEREST RATE$_t$	0.02257	***	0.02278	***
GDPG$_t$	-0.42148	***	-0.38363	***
T	0.02244	***	0.02317	***
-LOG LIKELIHOOD	-84335.95906	***	-83417.41346	***
CONSTANT	0.046005914	***	0.047419299	***
Test Asymmetric Impact				
(p-value)				
$\alpha + \beta = 0$	-		0.2409	
$\alpha - \beta = 0$	-		0.3768	

Tab. 4: Estimations Results of Equation (1): Part C.

Variables	(5)		(6)	
	Coeff.	Sig.	Coeff.	Sig.
Dependent Variable	$DEFAULT_{ijt+4}$ *(0/1)*		$DEFAULT_{ijt+4}$ *(0/1)*	
LOANG_{bt}-AVERAGE $\text{LOANG}_b(\alpha)$	0.00046 ***	***	0.00006	***
$\lvert LOANG_{bt} - AVERAGELOANG_b \rvert(\beta)$	-	-	-0.00070	***
BANK $\text{SIZE}_{b,t}$	1.29230	***	1.33032	***
OWN FOUNDS/TOTAL $\text{ASSETS}_{b,t}$	4.03234	***	4.88155	***
$\text{NPL}_{b,t}$-NPL_t	-0.16069	***	-0.07872	***
BORROWER $\text{RISK}_{f,t}$	1.94020	***	1.90044	***
LN(2+AGE AS $\text{BORROWER})_{f,t}$	-0.05088	***	-0.06173	***
LN(1+NUMBER OF BANK $\text{RELATIONSHIPS})_{f,t}$	0.13677	***	0.13413	***
$\text{COLLATERAL}_{l,t}$ (0/1)	-0.57640	***	-0.58958	***
LN(SIZE OF THE $\text{LOAN}_{l,t}$)	-0.08019	***	-0.07475	***
MATURITY_l 1Y-3Y (0/1)	0.04244	***	0.07358	***
MATURITY_l 3Y-MORE (0/1)	-0.48453	***	-0.56795	***
INTEREST RATE_t	-0.01308	***	0.00206	***
GDPG_t	2.41658	***	1.18897	***
T	0.01392	***	0.01020	***
-LOG LIKELIHOOD	-41431.50171	***	-48544.15863	***
CONSTANT	0.148602112	***	0.21297513	***
Test Asymmetric Impact				
(p-value)				
$\alpha + \beta = 0$	-		<.0001	
$\alpha - \beta = 0$	-		0.0248	

Tab. 5: Estimations Results of Equation (1): (Loan Growth Rate of Bank Introduced without Comparison to Its Average Value)

Variables	(1)		(2)		(3)	
	Coeff.	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**
Dependent Variable	$DEFAULT_{ijt+2}$ *(0/1)*		$DEFAULT_{ijt+3}$ *(0/1)*		$DEFAULT_{ijt+4}$ *(0/1)*	
LOANG$_{bt}$	0.00019	***	0.00021	***	-0.00041	***
BANK SIZE$_{b,t}$	0.24276	***	0.65198	***	1.41945	***
OWN FUNDS/TOTAL ASSETS$_{b,t}$	4.87076	***	2.49528	***	4.87747	***
NPL$_{b,t}$-NPL$_t$	0.17324	***	-0.16762	***	-0.07814	***
BORROWER RISK$_{f,t}$	1.99169	***	2.08752	***	1.89513	***
LN(2+AGE AS BORROWER)$_{f,t}$	-0.04335	***	-0.03194	***	-0.06141	***
LN(1+NUMBER OF BANK RELATIONSHIPS)$_{f,t}$	0.19419	***	0.17945	***	0.13671	***
COLLATERAL$_{l,t}$ (0/1)	-0.55819	***	-0.51004	***	-0.58765	***
LN(SIZE OF THE LOAN$_{l,t}$)	-0.06496	***	-0.08496	***	-0.07472	***
MATURITY$_l$ 1Y-3Y (0/1)	0.01362	***	0.25552	***	0.07282	***
MATURITY$_l$ 3Y-MORE (0/1)	-0.34167	***	-0.28884	***	-0.56704	***
INTEREST RATE$_t$	0.06036	***	0.02276	***	0.00466	***
GDPG$_t$	-2.01997	***	-0.44690	***	1.01642	***
T	0.00711	***	0.02247	***	0.00880	***
-LOG LIKELIHOOD	-152636.5752	***	-84334.14388	***	-48550.91107	***
CONSTANT	-0.195886775	***	0.040082082	***	0.17267998	***

Tab. 6: Countercyclical provisions effect on the amount of the loans: Counterfactual distribution

Without interaction

Effect	q_5	q_{10}	q_{25}	q_{50}	q_{75}	q_{90}	q_{95}
	Coeff.	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**
Dependent variable:	$LLoanA_{q,l,t}$						
TREATMENT	-10.91 ***	-9.45 ***	-6.96 ***	-6.25 ***	-6.22 ***	-6.93 ***	-8.18 ***
CONSTANT	14.72 ***	15.62 ***	16.95 ***	18.13 ***	19.37 ***	20.93 ***	22.18 ***

Interaction: Bank Size

Effect	q_5	q_{10}	q_{25}	q_{50}	q_{75}	q_{90}	q_{95}
	Coeff.	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**
Dependent variable:	$LLoanA_{q,l,t}$						
TREATMENT	-15.65 ***	-11.68 ***	-7.91 ***	-6.75 ***	-6.62 ***	-6.93 ***	-8.18 ***
Interaction							
BANK SIZE	0.32 ***	0.17 ***	0.77 ***	0.39 ***	0.31 ***	0.00	0.00
CONSTANT	14.72 ***	15.62 ***	16.95 ***	18.13 ***	19.37 ***	20.93 ***	22.18 ***

Interaction: Own Funds

Effect	q_5	q_{10}	q_{25}	q_{50}	q_{75}	q_{90}	q_{95}
	Coeff.	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**
Dependent variable:	$LLoanA_{q,l,t}$						
TREATMENT	-11.83 ***	-8.80 ***	-6.99 ***	-6.09 ***	-5.91 ***	-6.93 ***	-8.18 ***
Interaction							
OWN FUNDS	0.22	-0.19	0.10	-0.49	-0.89 **	-0.00	-0.00
CONSTANT	14.72 ***	15.62 ***	16.95 ***	18.13 ***	19.37 ***	20.93 ***	22.18 ***

Interaction: Bank-NPL

Effect	q_5	q_{10}	q_{25}	q_{50}	q_{75}	q_{90}	q_{95}
	Coeff.	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**	**Coeff.**
Dependent variable:	$LLoanA_{q,l,t}$						
TREATMENT	-11.66 ***	-8.06 ***	-8.12 ***	-7.14 ***	-6.57 ***	-6.96 ***	-8.24 ***
Interaction							
BANK-NPL	-0.27	0.11	-0.10 *	-0.75 **	-3.19	-0.00	0.00
CONSTANT	14.77 ***	15.69 ***	16.99 ***	18.19 ***	19.42 ***	20.96 ***	22.24 ***

A Appendix: Individual Provisions in Colombia: Countercyclical Component

The countercyclical component of individual provisions in Colombia is calculated according to four criteria: Quality, efficiency, fragility and loan growth.

A.1 Indicators

The indicators are computed according to the following formulas:

a) Quality: Real quarterly variation in the provisions of total lending portfolio of type B, C, D, and E.

$$(\Delta IndProv_{BCDE})_T = \frac{(Total\ Loan\ Portfolio\ Individual\ Provisions\ BCDE)_T}{(Total\ Loan\ Portfolio\ Individual\ Provisions\ BCDE)_{T-3}} - 1 \tag{2}$$

According to the grading of the loan portfolio, A, B, C, D, and E, this indicator takes into account all possible migrations from one grading to another.

b) Efficiency: Quarterly amount of net of recovery provisions (NRP) as a percentage from the total amount of quarterly interest revenue on lending portfolio and leasing:

$$(NRP/IxI)_T = \frac{(NRP\ accumulated\ during\ each\ quarter)_T}{(IxI\ accumulated\ during\ each\ quarter)_T} \tag{3}$$

This indicator tries to establish if the expenses in provisions associated to loan's deterioration from the bank, consume an important part from the revenues derived from the loan portfolio intermediation activity.

c) Fragility: Quarterly amount of net of recovery provisions (NRP) as a percentage from the total amount of quarterly amount of adjusted gross financial margin, $GFM_{adjusted}$:

$$(NRP/GFM_{adjusted})_T = \frac{(NRP\ accumulated\ during\ each\ quarter)_T}{(GFM_{adjusted}\ accumulated\ during\ each\ quarter)_T} \tag{4}$$

This indicator trries to establish if the provision's expenses use another sources different to those associated to the business of loan portfolio intermediation.

d) Credit Growth: annual rate of growth in gross loans portfolio, GL:

$$\Delta GL_T = \frac{GL_T}{GL_{T-12}} - 1 \tag{5}$$

A.2 Rule that defines the methodology for accumulating or releasing the countercyclical provisions.

If during three consecutive months the evaluation of the indicators shows that :

$$(\Delta IndProv_{BCDE})_T \geq 9\% \ and \ (NRP/IxI)_T \geq 17\% \ and$$

$$[(NRP/GFM_{adjusted})_T \leq 0 \ or \ (NRP/GFM_{adjusted})_T \geq 42\%] \ and \ \Delta GL < 23\%$$

the bank must compute the individual provisions using the releasing methodology, otherwise, it should use the accumulative methodology.

A.2.1 Accumulative methodology

The Individual Countercyclical Component, (ICC) should be computed as:

$$ICC_{i,t} = max\left(ICC_{i,t-1} * \left(\frac{Exp_{i,t}}{Exp_{i,t-1}}\right); (EL_B - EL_A)_{i,t}\right)$$

where $Exp_{i,t}$ corresponds to the obligation's (i) exposure at the time of the provision (t). $0 \leq \left(\frac{Exp_{i,t}}{Exp_{i,t-1}}\right) \leq 1$, and if it is higher than 1 it is assumed to be 1. The term EL_B is the expected loss computed using as probability of non-payment the Matrix established by the Superfinanciera which corresponds to a non-payment probability matrix for periods of bad times in the lending portfolio. Similarly, EL_A is the expected loss using the Matrix A which corresponds to a non-payment probability matrix for periods good times in the lending portfolio.

A.2.2 Releasing methodology

It is applied when a bank presents signals of lending portfolio deterioration that affects in important way its balance sheet. In this case, the (ICC) should be computed as

$$ICC_{i,t} = ICC_{i,t-1} - max\left\{RF_{i,t} \ ; \ ICC_{i,t-1} * \left(1 - \frac{Exp_{i,t}}{Exp_{i,t-1}}\right)\right\}$$

The releasing factor, $RF_{i,t}$ is given by

$$RF_{i,t} = \left(\frac{ICC_{i,t-1}}{\sum\limits_{active} ICC_{i,t-1}}\right)_m * (40\% * NRP_{IPC-m})$$

where,

NRP_{IPC-m} are the net of recovery provisions associated to the procyclical component in the type of lending portfolio (m).

$\sum\limits_{active} ICC_{i,t-1}$ is ICC in (t-1) of the sum over active obligations at the moment of the provision (t) in the type of lending portfolio (m).

$RF_{i,t} \geq 0$, in opposite case it is supposed to be zero.

If $\frac{Exp_{i,t}}{Exp_{i,t-1}} > 1$ it is supposed to be 1.

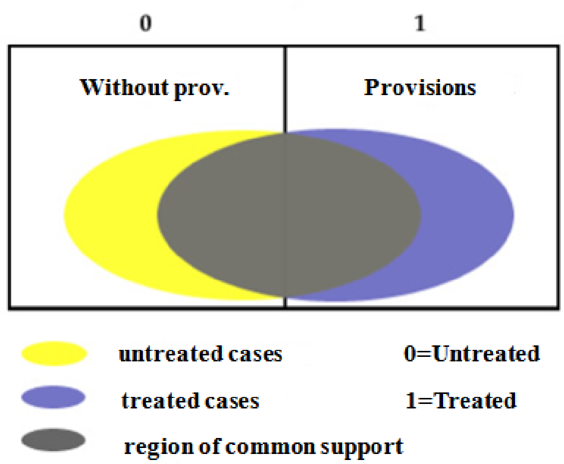
B Appendix: Propensity match scores

The goal of this methodology is to reduce the bias between treatment and control groups. In order to achieve a balance between the treated and untreated observations, or making sure they have similar distributions, it is necessary to ensure that the regions of the distributions that do not overlap are pruned from the data set. Therefore, in this set up, we use matching by means of the propensity score.

The procedure for estimating the impact of the countercyclical provisions on loans growth can be divided into three main steps: 1) Estimating the propensity score. 2) Choosing a matching algorithm that will use the estimated propensity scores to match untreated units to treated units, where units are bank loans amount granted to the firm. 3) Estimating the impact of the intervention with the matched sample and computing standard errors.

A propensity score is a probability value that provides information about the likelihood that an unit has received treatment given a set of covariates. This conditional probability is predicted by a probit model. The treatment of this study for loans is having countercyclical provisions (figure 1).

Fig. 1: Countercyclical Provisions



We use $Y_1$and Y_0 to denote the *potential outcomes* for a loan in presence and absence of the treatment, respectively. The observed outcome Y for a loan will be Y_1 if the loan is in the state of coutercyclical provisions and Y_0 otherwise. Let T be the treatment of the observed units, namely $T = 1$ for those with countercyclical provisions and X is the set of pre-treatment covariates.

Then, the observed outcome can be written as $Y = (1 - T)Y_0 + TY_1$. When a given unit is treated, then $T = 1$. Thus, the observed outcome for this unit will be $Y = 0Y_0 + 1Y_1 = Y_1$, which means that the observed outcome (Y) for treated loans is equal to the *potential outcome* (Y_1) in case of treatment . In this case, the potencial outcome in absence of treatment is not observed. And therefore, for a treated unit, Y_0 is the *counterfactual*. Similarly, when the unit is not treated, $T = 0$, and $(1 - T) = 1$, and thus $Y = Y_0$. In this case the counterfactual is Y_1.

Since it is impossible to re-run history or have perfect control when we have observational data, the propensity score is one way to isolate this causal effect. This assumes that all relevant differences between treatment and control groups are captured by the observables. If this assumption holds, treatment assignment is independent of outcomes. In other words, $(Y_0, Y_1) \perp T/X$.

On the other hand, the basic goal of matching is to find control units that are very similar to treated units. A central assumption of most matching techniques is that units are independent. In a time series context, this assumption is quite strong. Trying to reduce this problem we adapt in this paper a technique developed by Young (2008). Thus, we separate the dataset by periods in terms of *transitions to treatment*, then match observations within each period, and finaly recombine the pruned cross sectional data set into a TSCS (Time Series Cross Sectional) dataset.

We present table 7 with the bias reduction for a set of variables using this matched sample. As can be seen, the reduction was important in almost all variables. Moreover, the overall bias was reduced around 51.63%. We conclude that the balance between treatment group and control group is improved from the unmatched sample.

Finally, the results of the effect of the treatment on loan growth are presented in section 3.3.

Tab. 7: Comparing matching and unmatching samples

Variable	**Sample**	**Mean Treated**	**Mean Control**	**Mean Diff**	**% Bias Reduction**
BANK SIZE	Unmatched	0.111	0.082	0.029	
	Matched	0.130	0.117	0.012	57.19%
OWN FUNDS	Unmatched	0.040	0.060	0.020	
	Matched	0.033	0.030	0.012	36.83%
GDP	Unmatched	0.043	0.044	0.001	
	Matched	0.030	0.031	0.001	3.00%
IBR	Unmatched	2.572	1.642	0.930	
	Matched	3.819	3.807	0.012	98.72%
AGE	Unmatched	3.819	3.604	0.215	
	Matched	3.894	3.757	0.136	36.71%
BORROWER RISK	Unmatched	0.015	0.010	0.005	
	Matched	0.030	0.029	0.001	77.33%