Credit Pro-cyclicality and Bank Balance Sheet in Colombia*

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Abstract

The recent financial crisis has renewed the interest of economists, both at the theoretical and empirical level, in developing a better understanding of credit and its mechanisms. A rapidly growing strand of the literature views banks as facing funding restrictions that condition their borrowing to a risk-based capital constraint which, in turn, affects bank lending. This work explores the way banks in Colombia manage their balance sheet and sheds light into the dynamics of credit and leverage during the business cycle. Using a sample of monthly bank balance sheets for the period 1994-2012, we find not only that the Colombian banking sector is predominantly pro-cyclical, but also that the composition of bank liabilities provides important information to policy makers regarding the phase of the cycle of the economy. Shifts from low non-core liability ratios to higher ones during the upward phase of the leverage cycle could play the role of an early warning indicator of financial vulnerability. In addition, we find that bank heterogeneity matters and thus, an aggregate measure of bank leverage can mask successfully a fragile financial sector.

Keywords: banks, credit, leverage, non-core liabilities, balance sheet, business cycle, Colombia

JEL Classification Codes: E32, G21, G32.

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1 Introduction

This paper explores the way banks in Colombia manage their balance sheet and sheds light into the dynamics of credit. The idea is to see whether the link between credit dynamics, leverage and liability composition explains credit supply decisions. Evidence in this direction would help to understand credit fluctuations, identify possible signs of pro-cyclicality, and advance in the elaboration of a more appropriate view of the banking sector. This view is centered in the structural relationships between the two sides of the balance sheet, and would be a considerable improvement from the traditional interpretation that goes, mechanically, from money to credit. By using bank-level data, this work pays particular attention to the importance of heterogeneity within the banking system and the role it plays in the evolution of credit in the economy.

The recent financial crisis has renewed the interest of economists, both at the theoretical and empirical level, in developing a better understanding of credit and its mechanisms. A growing number of studies, drawing on a tradition that underscores the inherent instability of credit systems, show that credit lies at the heart of financial crises and that the latter may be the endogenous outcome of how credit is created in the context of decisions of numerous and heterogeneous agents [Aikman et al. [2011], Jorda et al. [2011], Talylor [2012]].

Very briefly, the inherent instability of credit results from the feedback between credit fluctuations and changes in collateral prices. This relationship is best approached in terms of what is known in the literature as leverage cycles [Geanakoplos [2009], Jorda et al. [2011]].

Various strings and lines of research can be pursued in order to test the validity of these ideas and try to find empirical support for them under different scenarios. Among such lines, the present paper follows recent strands of the literature that directly connect the dynamics of credit to the behavior of banks, going beyond mere quantities and looking at their entire balance sheet, including assets, liabilities, their composition, and leverage) [Schularick and Taylor [2010]].

More specifically, recent interesting work builds on a formal model in which financial intermediaries manage their balance sheet in a way that is consistent with, and responds to, their credit supply decisions [Adrian and Shin [2008], Adrian and Shin [2011], Adrian and Shin [2012]; Adrian et al (2010); Adrian and Boyarchenko [2012]]. The model in question is, briefly put, a model of credit supply and credit risk, where a bank maximizes profits subject to a value-at-risk constraint. This means that banks, and financial intermediaries in general, face funding restrictions that condition their borrowing to a risk-based capital constraint which, in turn, affects bank lending. Changes in the size and composition of balance sheets are derived from credit decisions taken by banks. There is thus a “lending” or “balance sheet capacity” of banks determined by risk and regulatory considerations, and banks expand their lending so as to make full use of this capacity when risk perceptions improve. As this happens, balance sheets grow, leverage increases and lending standards deteriorate. In other words, pro-cyclical leverage is closely tied to a risk-based capital constraint.

Along these lines, Hahm et al. [2011a]explain how lending booms coincide with changes in the compositions of bank liabilities or shifts from “core” (basically retail deposits) to “non-core” liabilities. The nature of non-core liabilities varies from country to country and depends, among other things, on the characteristics of the financial sector and the nature of the credit system. Some key insights about the notion of non-core liabilities in the literature can be highlighted briefly. What lies in the background of these ideas are two basic findings of previous research:

1. In credit booms, increases in lending outstrip the funds available to banks through retail deposits of household savers, or core liabilities, and banks have to resort to other types of funding.

2. This funding, which comprises non-core liabilities, is closely linked to financial vulnerability.

In light of these findings, the expansion of balance sheets, driven by the need to use up the enlarged lending capacity that results from more favorable measured risk perceptions, moves banks to resort to other sources of funding different from core liabilities, as the latter do not respond speedily enough to the needs of banks. Credit (or the size of the balance sheet), leverage and the composition of bank liabilities are thus part of the same process.

In the case of emerging market economies, which is the focus of the paper by Hahm et al. [2011a], banks are the most important financial intermediary and wholesale funding markets are not well developed. For these economies the authors underline the crucial role of international capital flows and short-term funding in foreign exchange as a key component of non-core liabilities of banks, as well as the changes in their weight across the various phases of credit cycles.

The relevance of the link between credit dynamics and liability composition has also been highlighted by other authors. Schularick and Taylor [2010] for example, show how, for a sample of developed countries, the upward trend observed since 1945 in the ratio of bank assets to broad money is the other side of a simultaneous increase in funding of banks via non-monetary liabilities. Shin [2011], on their part, find that monetary aggregates, to the extent that they reflect the size of non-core and core liabilities, convey information on the stage of the financial cycle. Kim et al. [2012] study the relationship between cross-border banking and the composition of monetary aggregates in terms of core and non-core liabilities of banks. The authors derived from here information signaling vulnerability to financial crises.

The above setting has also been successfully applied in empirical studies of scenarios that may give rise to credit booms, financial instability and, eventually, financial crises. The key concept here is pro-cyclical leverage, a phenomenon that derives from the behavior of banks in their credit supply decisions along the lines of the model referred to above [Shin [2011], Adrian and Shin [2012], Adrian and Shin [2008]].

Hahm et al. [2011b], using aggregated information for a sample of emerging and developing economies, analyze the link between various definitions of non-core bank liabilities and different measures of crises. The authors find that the non-core liabilities have a strongly predictive power for both currency and credit crises. These results indicate that credit booms are reflected in the composition of liabilities. In a related exercise, focused on pro-cyclicality of leverage in the Canadian banking system, Damar et al. [2012] find that banks that rely more on non-core liabilities (wholesale funding) exhibit a higher degree of leverage pro-cyclicality. Non-core liabilities are a sign of vulnerability in banks' balance sheets. Studies that rely on bank-level data, as is the case of this paper, are particularly suitable to exploit heterogeneity within the banking sector when conducting analyzes of how banks manage their balance sheets. For these purposes, it is clear that heterogeneity refers to differences in the way banks manage their portfolio [Adrian and Shin [2008]]. Two types of banks or bank behavior can be identified depending on the relationship between leverage and assets or balance sheet size:

- Banks that seem to target a constant leverage ratio

- Banks that exhibit pro-cyclical leverage or a positive relationship between changes in leverage and changes in total assets

This heterogeneity in balance sheet management practices has been linked in the literature with the degree of reliance on the capital market and mark-to-market practices. Pro-cyclical leverage might have more incidence in market-based than in bank-based credit systems [see Damar et al. [2012] for Canada and Adrian and Shin [2008] for the USA]. In Colombia, with a credit-system centered in banks, bank heterogeneity, as defined above, could be explained from differential access to markets for funding (bank size, for example). This issue will be dealt with in the paper. The division of banks into those that target a leverage ratio and those with pro-cyclical leverage should not blur the fact that leverage ratios vary widely both between banks and in time, depending on the different phases of the business cycle.

2 Data and empirical regularities

The empirical analysis of the role of leverage in the dynamics of credit and bank assets conducted in this paper, relies on a balanced panel data set which consists of financial intermediaries operating in Colombia from January 1994 to December 2011. We use monthly data that capture the highest available frequency at which we can study the interaction of macroeconomic variables (economic activity, inflation and interest rates) with the banks balance sheet information.

2.1 Sample

Bank balance sheet data come from the Unique Accounting Plan (PUC) of the Financial Superintendence, which contains specific balance-sheet information of all banks. Our database contains detailed accounting information of 29 banks, all grouped in what we call "consolidated banking system". We excluded Special Financial Entities (EFE's) to avoid double accounting in loans, but also Financial Cooperatives, Financial Corporations, and Commercial Financing Companies, and focus on banks, the core of our analysis.

We end up with a panel data which is large across time but small across agents. The long sample period includes two credit booms, as defined in Guarín et al. [2012], as well as other structural macroeconomic and policy regime changes. The years 1994 to 1998 were characterized, as in many emerging countries, by a macroeconomic boom after the structural reforms (including a trade and capital account liberalization), and the stabilization programs of the beginning of the 90s: widening fiscal and external deficits, rapid credit, investment and consumption growth and soaring asset prices, in a heavily intervened foreign exchange market and shallow financial markets. The South East Asia financial crisis led to a Sudden Stop of capital inflows and affected Colombia with particular strength. Currency, financial and macroeconomic crises hit the economy in 1999 with protracted effects. The financial crisis of the end of the 90s was characterized by the failure of many financial institutions, as Gómez-Gónzalez and Kiefer [2009] recount. After failures, mergers, and acquisitions, the financial system shrank from 39 commercial banks in 1998 to 27 three years later.

By 1999, the country allowed the exchange rate to float more freely and embarked in a fiscal consolidation process. And by 2001, Colombia adopted an Inflation Targeting regime and strengthened financial regulation, to mention a few important changes. Five years later the economy was growing at the fastest pace in decades, public debt appeared sustainable, the financial sector showed no evident signs of weakness and inflation was low and stable. When the global financial crisis hit the economy, it almost stopped growing in 2009 and the currency depreciated temporally but there was no financial crisis.

Despite all these significant changes, we did not restrict the sample across time to concentrate in a particular period, as we want to focus on the dynamics of bank balance sheets and leverage along the business cycle. As we will explain in the model specification section, we will do our best to control for several of these factors, in particular the monetary policy regime change.

Instead, we chose to restrict our sample across banks. We did so because the sample is not large and homogeneous enough to perform statistical inference with a great deal of confidence along that dimension, and using that information could bias our analysis. For instance, there are four big banks that hold in average sixty percent of the banking system total assets during our sample period, and thus dominate the industry: Bancolombia, Davivienda, Bogotá, and BBVA. This means that the rest are medium and small banks, the latter being quite specialized institutions. This has been particularly evident in the last ten years, period that has seen the appearance of many small and specialized banks, such as the WWB Bank, which focuses on women entrepreneurs, and many others that specialize in micro and small enterprises. Balance-sheet accounts and management of these banks are quite different from other banks, and may thus introduce noise and outliers to our analysis, specially considering our small sample across individuals. We addressed this problem by grouping the banks that in April 2012 had a share of the consolidated banking system assets of less than 2.5%, in what we call "Small Banks", accounting for 5% of total assets.[1]

One bank deserves special treatment: Banco Agrario. It was created in 1999, following the liquidation of Caja Agraria, a public financial institution focused on the agricultural sector that had to be intervened as a result of malpractices and mismanagement. The transfer of assets and safe loan portfolio to Banco Agrario was likely to impact its leverage during this period. Furthermore, data available for this bank before 1999 include 53 out of 60 months where equity, and thus leverage, were negative, reaching a trough in August 1994, when the leverage ratio was -564.2. Atypical observations like this are not an indicative of the debt and other liabilities that a bank uses to finance its assets, and would bias the consolidated banking system leverage in this period, calculated as a weighted average (by assets) of the leverage of all banks.

In addition, Banco Agrario is the only bank in the database that is fully owned by the state, as 99 percent of its stocks shares are held by the Treasury. This bank is affiliated to the Ministry of Agriculture and Rural Development and it is arguable that its balance-sheet accounts are not marked to market as they may not reflect the bank's current financial situation, specially for the period before 2000. Also, the bank may be prone to allocate resources differently from the rest of the banks in the sample, as was the case of the extinct Caja Agraria for a long period of time. Thus, to avoid all these non-market factors, and the ones inherent to any liquidation, we kept Banco Agrario out of the analysis.

This grouping of banks and the exclusion of Banco Agrario left us with a sample of fourteen banks, four of them classified as foreign: Santander, Citibank, Sudameris, and BBVA. Overall, the data set contains 3024 bank-month observations.

[1]The banks that were grouped under this label are the following: ABNAmro, Andino, Bancamía, HSBC, BankBoston, Coomeva, Estado, Falabella, Finandina, Pacífico, Pichincha, Procredit, Selfin, Standard Charter, Uconal, and WWB.

2.2 Leverage

A key variable in our analysis is bank leverage. We measure the leverage ratio of bank i at date t as $l_{i,t} = a_{i,t}/e_{i,t}$, where a_i represents the bank's total assets and e_i its equity. Small banks' leverage was calculated by first changing the months of negative leverage to missing values. Assets for these months were considered to be zero. Leverage for each month in the sample was then calculated as an asset weighted average of the leverage of each of the sixteen small bank observations:

$$l_{St} = \sum_{i=1}^{16} \omega_{it}^{S} l_{it}^{S}$$

where $l_{it}^{S} = a_{it}^{S}/e_{it}^{S}$ denotes the leverage ratio of a bank i, which has been classified as small, at time t and a_i^s denotes its assets and e_i^s its equity; ω_i^s is the share of the assets of the small bank i within the group of all small banks. It is worth noting that when equity is negative, we set the assets of negative-leverage months to zero. Consolidated banking system's leverage was calculated in a similar way, as an asset weighted average of the leverage of the 14 banks in the sample, excluding Banco Agrario.

2.3 Non-core liabilities

The second key and perhaps less known variable in the analysis is non-core liabilities. As stated earlier there is no single definition of this variable and it varies from country to country, depending on the structure of the banking and financial systems. This paper uses a working definition of core and non-core liabilities that fits with the type and development of the banking sector in Colombia. This definition has been drawn from a wider and growing literature that aims at building a better understanding of balance sheet management, bank liability composition and financial vulnerability.

For example, Adrian and Shin [2011] analyze balance sheet management by commercial and investment banks in developed economies with a capital market-based credit system, and stress that in such cases non-core liabilities are basically made up of wholesale funding, in particular repurchase agreements and commercial paper. The authors find that rapid asset growth and greater reliance on non-core liabilities are closely related to systemic risk and interconnectedness between banks.

The notion of non-core liabilities for an emerging economy may be different. Kim et al. [2011] study the problem of liability composition in open economies with bank-based credit systems, with a particular emphasis in Korea. In addition to stressing the links between the relative importance of non-core liabilities and financial pro-cyclicality, the work underlines those between these liabilities and the compression of risk premiums in the credit market. When discussing measures of non-core liabilities, the authors opt for a criterion based on the holder rather than on the type of the liability in question, and emphasize the importance of liabilities to foreign creditors in the definition of non-core liabilities of banks in open emerging economies.

A first general definition of non-core liabilities in these economies would then be the sum of wholesale bank funding and foreign exchange liabilities. In the case of Korea, this comprises six categories of bank liabilities: foreign exchange borrowing, debt securities, repurchase agreements, promissory notes (two types), and certificates of deposit.

For their analysis of the potential of non-core liabilities to predict vulnerability to crises for a sample of countries, the authors use two definitions:

1. Non-core 1: liabilities of banks to the foreign sector + liabilities of banks to the non-banking financial sector

2. Non-core 2: liabilities of banks to the foreign sector + (M3 – M2)

Shin [2011] further elaborate on the justification for including liabilities to foreign creditors as part of non-core liabilities of banks in open emerging economies. The argument runs in terms of the volatility of the various types of bank liabilities. Whereas claims to the household sector or retail deposits, which depend on household wealth, tend to be stable, wholesale funding exhibits a high degree of volatility. In emerging economies open to capital flows, short-term foreign-currency denominated bank liabilities, usually very volatile, play a central role in credit booms and should be included as part of non-core liabilities. With foreign exchange liabilities and wholesale bank funding as comprising non-core liabilities, the authors find that the latter are closely related to measures of risk appetite, such as credit spreads.[2]

Hahm et al. [2011a] show that the composition of bank liabilities has evolved from country to country and across time. The close link that exists between monetary aggregates and bank liability composition, that characterizes bank-base credit systems, is not observed with the same strength in countries with capital market-based credit systems, in which wholesale funding has been gaining importance *vis a vis* deposit-based funding. As a result of the rapid evolution of financial systems in the recent past, there has been a move to greater reliance on interbank markets, commercial paper and asset-backed securities in the funding of banks.

In the case of open emerging economies, as mentioned above, the growing incidence of international capital flows explains the role of foreign exchange-denominated liabilities of banks in these economies, with crucial implications for financial stability considerations and macroprudential policies.

Along these lines, the authors put forward the hypothesis that the degree of financial pro-cyclicality is amplified by the expansion and shrinkage of non-core liabilities. To test this hypothesis, they apply to the Korean banking system a definition of core liabilities as liabilities due to an ultimate domestic creditor, and of non-core liabilities as those due to either an intermediary or to a foreign creditor, and obtain interesting findings:

1. Greater GDP elasticity of non-core versus core bank liabilities.

2. A semi-elasticity of non-core bank liabilities with respect to contemporaneous policy rate that is not statistically different from zero, while the corresponding semi-elasticity for core liabilities is high and significant and of a negative sign. This, the authors argue, calls into question the role of domestic monetary policy in containing excessive growth in non-core liabilities.

3. A negative and statistically significant semi-elasticity of non-core bank liabilities with respect to US policy rate, which means that global liquidity conditions play an important role in the build up of non-core liabilities in the upward phase of credit cycles.

[2] Nonetheless, the authors tried with different measures for non-core liabilities and the results were robust for different alternatives.

Kim et al. [2011] explore the extent to which an interest rate-oriented monetary policy framework accelerates financial pro-cyclicality through the provision of high-powered money on an on-demand basis aimed at keeping short-term interest rates as close as possible to the policy rate. For this the authors define core assets of banks as claims on the private sector, and non-core bank liabilities as bonds, liabilities to other banking institutions, foreign liabilities, etc. They conduct an econometric exercise for 14 countries (Colombia included) for the period 2002-2009. The work finds that increases in non-core liability growth have a positive effect on core asset, monetary base and M2 growth. The authors conclude from here that, when the central bank increases the money supply, private credit via non-core liabilities increases rapidly. In general, the finding of the paper is that non-core liabilities contribute to explain growth of both private credit and monetary aggregates.

In our work we measure core liabilities (at the bank level) as all the deposits included in the broad money supply (M3), except for CDT and bonds in domestic currency. These last two items are subject to reserve requirements but are marketable and, therefore, part of the non-core liabilities. CDT and bonds in both domestic and foreign currency and liabilities denominated in foreign currency are then part of non-core liabilities.[3]

We did not consider the following items as part of either core or non-core liabilities: Liability position in derivatives (code 23 of PUC), liabilities with other domestic and foreign banks and international organizations in domestic currency (code 24 of PUC), Estimated liabilities and provisions (code 28 of PUC), and Bonds mandatory convertible into shares (code 29 of PUC).

While Figure 1 shows the evolution of the non-core liabilities of the Colombian banks in the last two decades, Figure 2 presents their main components. It is quite clear that the importance of non-core liabilities has increased in the last two decades and that they appear to exhibit a cyclical pattern. Once again, we also see that there is a wide dispersion across intermediaries regarding the evolution of alternative financing instruments, which may reflect their different financial management policies, attitudes towards risk, access to different markets, among other aspects. We study these issues in more detail in the next section.

[3] Most of the information is classified under code 2 of the Unique Accounting Plan (PUC) of the balance sheets for commercial banks.

Figure 1: Noncore Liabilities across Colombian Banks

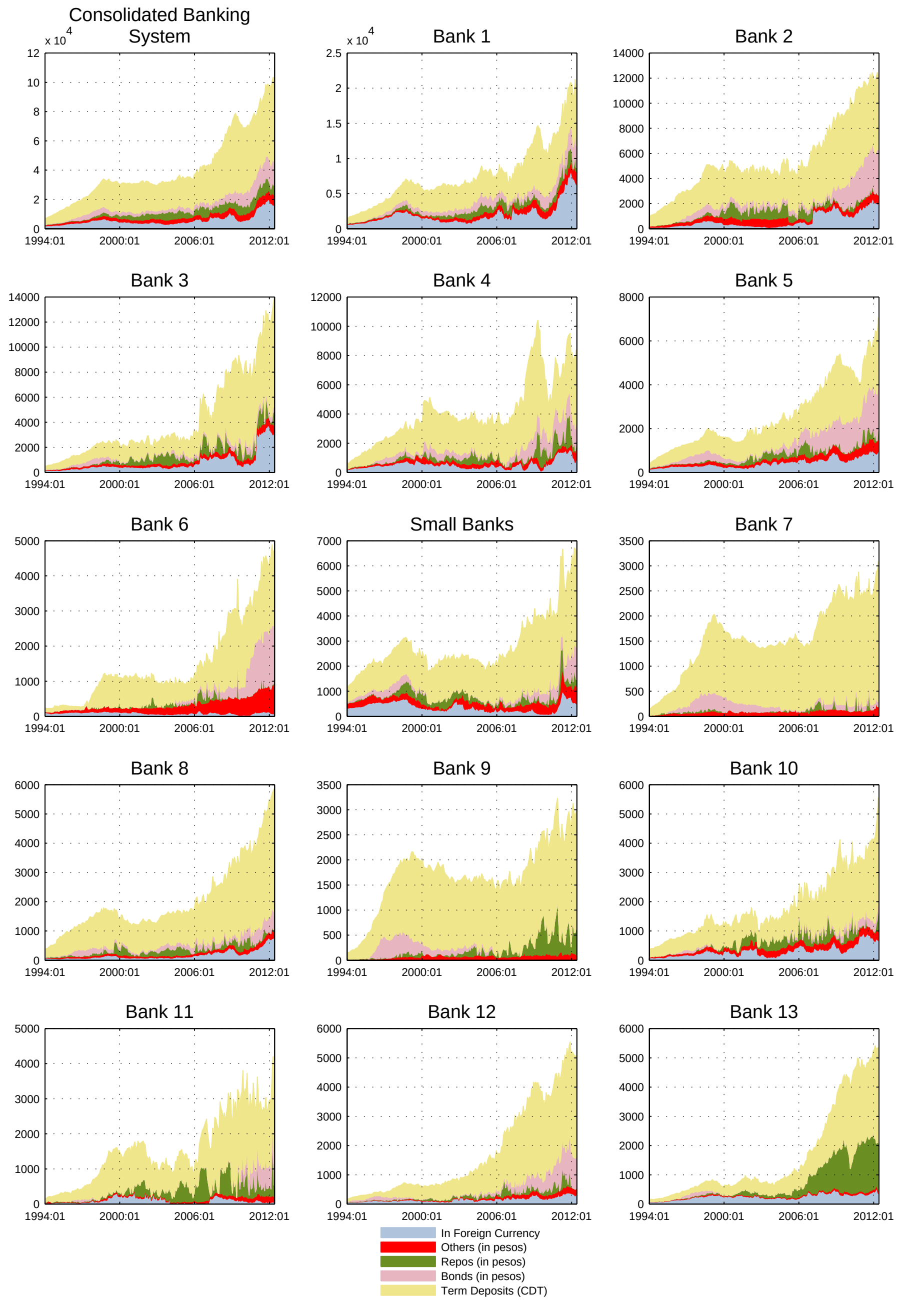
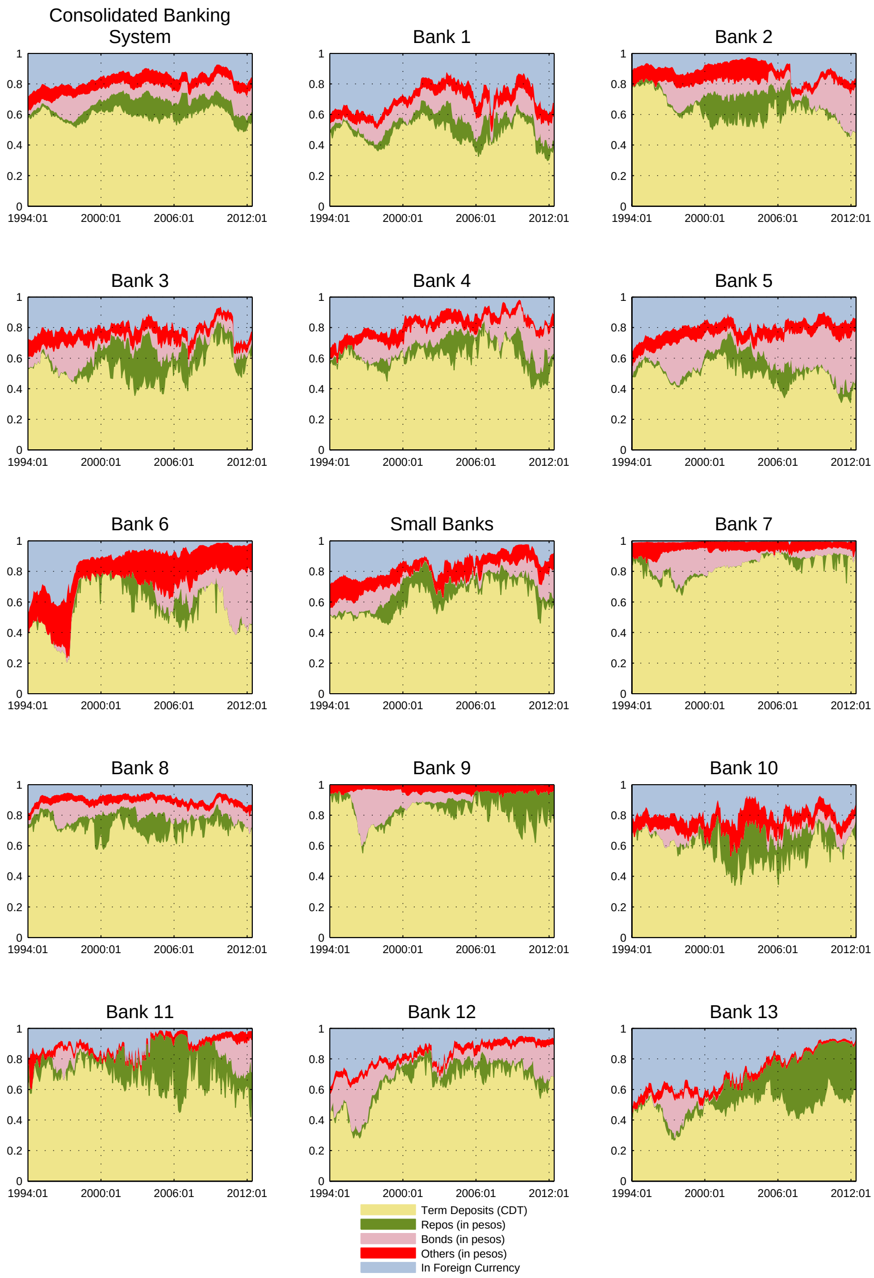


Figure 2: Composition of Noncore Liabilities across Banks



2.4 Some Stylized Facts

To try to overcome the fact that our sample is small across banks, we do not rely exclusively on the results of our estimated econometric model. Before diving into the econometrics, we perform different quantitative exercises to illustrate the importance of bank heterogeneity in understanding the dynamics of balance sheet management and credit dynamics.

Many studies take the aggregate leverage as an indicator of the degree of financial "heat" in the banking system and the economy. A quick look at the evolution of the distribution of banks' leverage, presented in the top panel of Figure 3, shows at least the following facts:

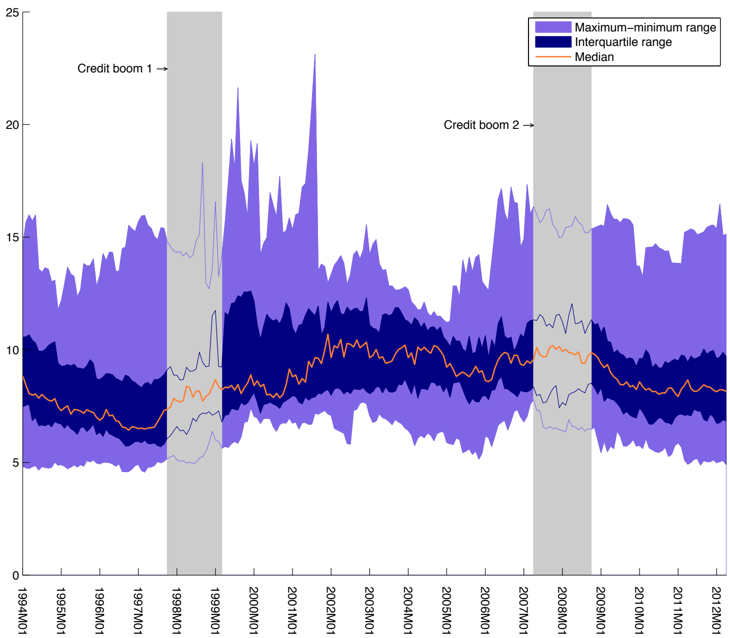
1. While the 1994-2011 median fluctuates around 8.8, the upper quartile of the distribution almost doubles this figure and the lower quartile is a small fraction of it.

2. Measured as either the inter-quartile range or as the max-min difference, leverage dispersion decreased between 2001 and 2005, period in which new financial regulation was introduced, but has increased thereafter.

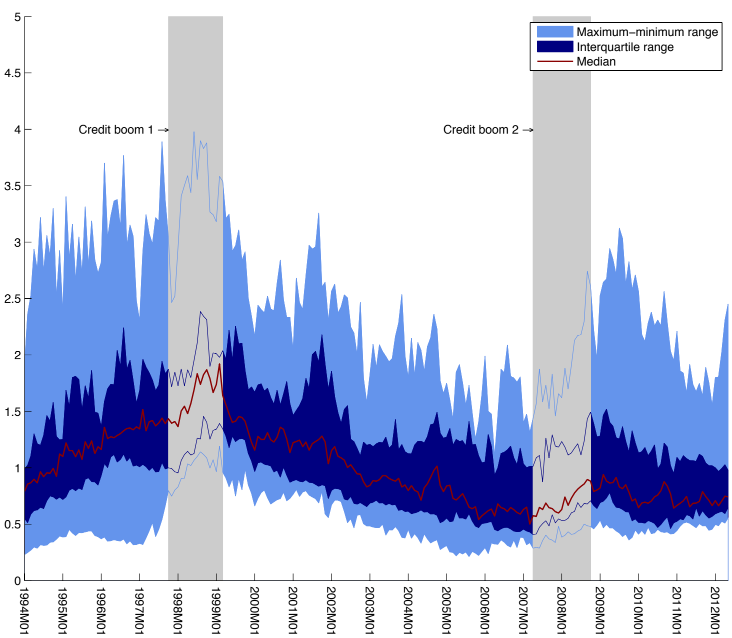
3. Leverage dispersion increased during the two credit boom episodes (1997:10-1999:03 and 2007:04-2008:10) as well as during the previous months.

Figure 3: Colombian Banks Leverage and NC2C Ratio by Quartils

(a) Leverage



(b) NC2C



A similar pattern can be traced when we inspect the composition of liabilities, measured as the ratio of non-core to core liabilities, in the bottom panel of Figure 3:

1. The median of this ratio fluctuates between 0.5 and 1.5. This means that the value of non-core liabilities expand and contracts significantly and quickly.

2. The dispersion, measured as either the inter-quartile range or as the max-min difference, is also large and volatile. The upper quartile more than doubles the median and the lower one can at times be

half of it.

3. Prior to the first credit boom (1997:10-1999:03) and during its development, non-core liabilities dispersion grew and become larger.

4. After the crisis, dispersion was reduced even coming into the second credit boom (2007:04-2008:10). However, during its development dispersion increased significantly and stayed larger thereafter.

This suggests that there is a wide dispersion in the degree of leverage between banks as well as in the composition of their liabilities. Focusing exclusively on central tendency measures may be misleading, since highly leveraged intermediaries co-exist with low-leveraged ones. This reinforces our prior that studying bank balance-sheets in detail may be a fruitful avenue to gain a deeper understanding of the business cycle.

As a first approximation to the relationship between leverage, bank liability composition and the credit cycle, we start by classifying banks by ownership (foreign or national), size (share in total assets) and business segment (commercial, consumer or mortgage loans). For each group we compute the leverage ratio, the monthly growth rate of total assets, and the non-core to core liabilities ratio. Also, across time, we split the sample in three: the full period 1994-2011 and the two credit booms. Furthermore, we take not only those months of the credit booms but also a 3-year window before, and after each boom. Table 1 shows the results. From the calculations we observe at least the following facts:

- The average leverage ratio for the banking system is 8.8 and there is no prominent difference in the 1994-2011 average leverage by nationality or the size of banks. Nonetheless, there are differences by business segment: mortgage banks have an average leverage of 11.2, commercial banks of 8.5 and consumer banks of 6.5. These differences do not change during and around the two credit booms.

- The average monthly growth rate of total assets (in real terms) for the banking system during the period of study is 0.5%. There are no significant differences by nationality, size or business segment. This is expected to be so since asset (month-to-month) growth displays large volatility. From the behavior of credit growth one can see that the two credit booms were different. While the first boom was preceded by rapid mortgage and consumption loans and a collapse of credit afterward, the second was preceded by rapid consumption and commercial credit growth and was not followed by a collapse in credit.

- The 1994-2011 average non-core to core liabilities ratio of the banking system is about one. In foreign consumer-loan oriented banks it tends to be higher than in national commercial and mortgage oriented banks. Furthermore, small banks clearly show (on average) a larger share of non-core liabilities.

A natural question to ask is whether these differences across types of banks reveal alternative ways to manage balance sheets and how these practices are related to credit dynamics. As pointed out by Adrian and Shin [2011], evidence for the United States suggests that the balance sheet management of financial intermediaries reveals that equity is sticky and the asset size of the bank is determined by the degree of leverage. The logic is that, if by definition, the leverage of bank i at time t is

$$l_{it} = \frac{a_{it}}{e_{it}}$$

Table 1: Averages of Some Indicators of Colombian Banks' Balance Sheets

		Credit boom 1 (1997:10-1999:03)							Credit boom 2 (2007:04-2008:10)						
	Sample	3bf	2bf	1bf	during	1af	2af	3af	3bf	2bf	1bf	during	1af	2af	3af
Leverage															
All Banks	8.79	7.75	7.64	7.58	8.38	9.49	9.61	9.72	9.01	8.95	9.20	9.25	8.79	8.36	8.21
Foreign Banks	9.05	6.69	6.37	6.00	7.06	8.26	8.55	8.84	9.96	10.32	10.72	11.17	10.87	10.30	10.28
National Banks	8.71	8.00	7.95	7.96	8.60	9.45	9.77	9.91	8.76	8.54	8.75	8.65	8.18	7.82	7.66
Commercial Banks	8.48	7.02	6.83	6.68	7.82	8.88	9.07	9.25	8.92	8.88	9.16	9.22	8.84	8.35	8.16
Consumer Banks	6.55	5.99	5.77	5.67	7.01	8.02	7.80	7.59	6.36	6.47	7.18	7.05	5.96	5.87	5.79
Mortgage Banks	11.20	11.98	12.11	12.36	11.45	13.08	13.03	12.96	10.47	10.24	10.22	10.31	9.24	9.25	9.31
Big Banks	8.24	6.98	6.78	6.58	7.68	8.55	9.03	9.21	8.49	8.35	8.58	8.65	8.31	7.86	7.66
Medium Banks	9.49	8.67	8.55	8.49	8.85	10.84	10.12	10.10	10.07	9.98	10.18	10.41	9.37	8.83	8.63
Small Banks	9.65	8.98	9.24	9.69	10.08	10.54	10.73	10.80	9.30	9.52	9.96	9.62	9.48	9.29	9.41
Monthly change in assets (percentage)															
All Banks	0.51	0.52	0.38	0.61	−0.24	−0.65	−0.56	−0.34	1.03	1.19	1.18	1.01	0.64	0.75	0.95
Foreign Banks	0.49	0.51	0.33	0.28	−0.25	0.62	0.12	−0.00	1.15	1.48	1.22	1.15	0.51	0.46	0.63
National Banks	0.54	0.57	0.45	0.69	−0.10	−0.94	−0.65	−0.35	0.99	1.08	1.10	0.89	0.68	0.83	1.02
Commercial Banks	0.52	0.41	0.27	0.49	−0.34	−0.58	−0.53	−0.27	1.04	1.17	1.09	1.08	0.57	0.72	0.97
Consumer Banks	0.71	0.97	1.21	2.29	2.48	−0.42	0.44	−0.02	2.00	2.40	3.28	0.02	0.88	0.36	0.23
Mortgage Banks	0.42	1.02	0.88	1.00	−0.24	−1.12	−1.02	−0.78	0.56	0.90	1.01	0.74	1.02	1.02	0.97
Big Banks	0.51	0.52	0.37	0.50	−0.38	−0.45	−0.43	−0.22	0.92	1.04	1.15	0.89	0.45	0.70	1.00
Medium Banks	0.44	0.27	0.16	0.56	−0.37	−1.07	−1.01	−0.63	0.96	1.20	0.94	1.17	0.69	0.75	0.91
Small Banks	0.64	0.99	0.87	1.12	0.43	−0.74	−0.37	−0.32	1.49	1.69	1.58	1.14	1.16	0.85	0.82
NC2C ratio															
All Banks	1.00	1.18	1.24	1.26	1.51	1.41	1.34	1.29	0.71	0.67	0.65	0.75	0.92	0.85	0.82
Foreign Banks	1.22	1.27	1.34	1.38	1.65	1.72	1.68	1.66	0.85	0.81	0.79	0.97	1.41	1.28	1.20
National Banks	0.95	1.16	1.22	1.25	1.52	1.37	1.26	1.20	0.69	0.64	0.62	0.69	0.80	0.75	0.73
Commercial Banks	0.97	1.19	1.23	1.24	1.46	1.32	1.26	1.23	0.68	0.64	0.63	0.72	0.89	0.82	0.80
Consumer Banks	1.49	1.78	1.82	1.90	2.56	2.63	2.45	2.34	0.95	0.82	0.87	0.97	1.18	1.14	1.04
Mortgage Banks	1.03	1.06	1.17	1.28	1.56	1.59	1.44	1.35	0.87	0.83	0.77	0.86	1.01	0.96	0.91
Big Banks	0.89	1.05	1.11	1.13	1.37	1.30	1.24	1.19	0.61	0.56	0.53	0.62	0.79	0.71	0.70
Medium Banks	0.88	1.17	1.20	1.17	1.37	1.26	1.14	1.07	0.61	0.58	0.56	0.65	0.72	0.67	0.66
Small Banks	1.57	1.70	1.81	1.88	2.23	2.01	1.93	1.94	1.26	1.19	1.19	1.31	1.58	1.52	1.43

Table 1: (Continued) Averages of Some Indicators of Colombian Banks' Balance Sheets

		Credit boom 1 (1997:10-1999:03)							Credit boom 2 (2007:04-2008:10)						
	Sample	3bf	2bf	1bf	during	1af	2af	3af	3bf	2bf	1bf	during	1af	2af	3af
Monthly change of credit denominated in all currencies (percentage)															
All Banks	1.20	1.90	1.77	1.76	0.84	0.24	0.35	0.48	1.27	1.35	1.07	1.27	0.96	1.04	1.21
Foreign Banks	1.12	1.77	1.63	1.29	0.35	1.70	1.15	0.86	1.37	1.73	1.04	1.43	0.89	0.86	0.93
National Banks	1.24	1.97	1.86	1.87	1.09	−0.11	0.17	0.40	1.23	1.23	1.06	1.21	0.96	1.07	1.27
Commercial Banks	1.20	1.79	1.63	1.59	0.69	0.34	0.37	0.54	1.29	1.32	0.97	1.31	0.95	1.03	1.24
Consumer Banks	1.34	1.93	2.15	2.29	3.48	1.09	1.77	1.06	1.99	2.10	2.21	0.68	0.23	0.52	0.39
Mortgage Banks	1.14	2.51	2.43	2.54	1.14	−0.51	−0.20	0.02	0.89	1.32	1.44	1.15	1.26	1.18	1.17
Big Banks	1.17	1.83	1.69	1.56	0.62	0.40	0.41	0.51	1.08	1.12	0.92	1.19	0.85	1.02	1.31
Medium Banks	1.22	1.86	1.69	1.96	1.00	−0.17	0.09	0.45	1.32	1.48	1.09	1.29	1.08	1.06	1.11
Small Banks	1.29	2.26	2.23	2.11	1.32	0.32	0.48	0.42	1.86	1.99	1.57	1.50	1.17	1.04	1.02
Annual change of credit denominated in all currencies (percentage)															
All Banks	14.22	23.87	23.01	22.76	16.09	2.62	4.55	5.24	15.78	15.97	15.67	15.02	13.70	11.86	14.08
Foreign Banks	13.13	23.43	22.55	21.49	11.57	5.33	12.90	9.81	15.57	17.67	16.32	17.09	15.61	9.49	10.76
National Banks	14.64	24.32	23.68	23.52	17.95	3.37	3.29	4.48	15.83	15.44	15.40	14.14	13.22	12.46	14.88
Commercial Banks	14.22	22.54	21.60	20.94	14.39	1.60	4.52	5.23	16.49	16.01	14.77	15.13	14.13	11.82	14.41
Consumer Banks	16.11	24.29	23.69	26.49	41.06	28.76	25.71	21.28	20.50	26.12	35.73	11.85	6.74	7.06	6.37
Mortgage Banks	13.14	30.91	30.28	31.44	20.05	1.15	−1.31	0.59	8.89	12.01	15.37	15.11	12.38	13.53	13.65
Big Banks	13.78	23.15	22.40	21.50	13.62	1.46	5.68	5.13	13.99	13.20	12.97	13.44	13.59	11.16	14.85
Medium Banks	14.33	22.77	21.01	21.16	18.81	0.39	−0.11	3.82	16.28	17.14	15.42	16.46	12.25	12.48	13.11
Small Banks	15.50	28.68	29.17	30.46	20.06	9.74	7.17	7.47	21.38	24.12	25.42	18.28	16.08	13.15	12.66

Note: Banks were organized along these groups: Mortgage banks: AVVillas, BCSC, Colpatria; Consumer banks: Citibank; Commercial Banks: the remaining; Big Banks: Bancolombia, Davivienda, Bogotá, BBVA; Medium Banks: Occidente, Popular, Small Banks, BCSC, Colpatria; Small Banks: AVVillas, Santander, Citibank, Helm Bank, Sudameris. This classification was done by taking an average of the shares of the different types of portfolio within the total loan portfolio, for a 5 year time window around both credit booms.

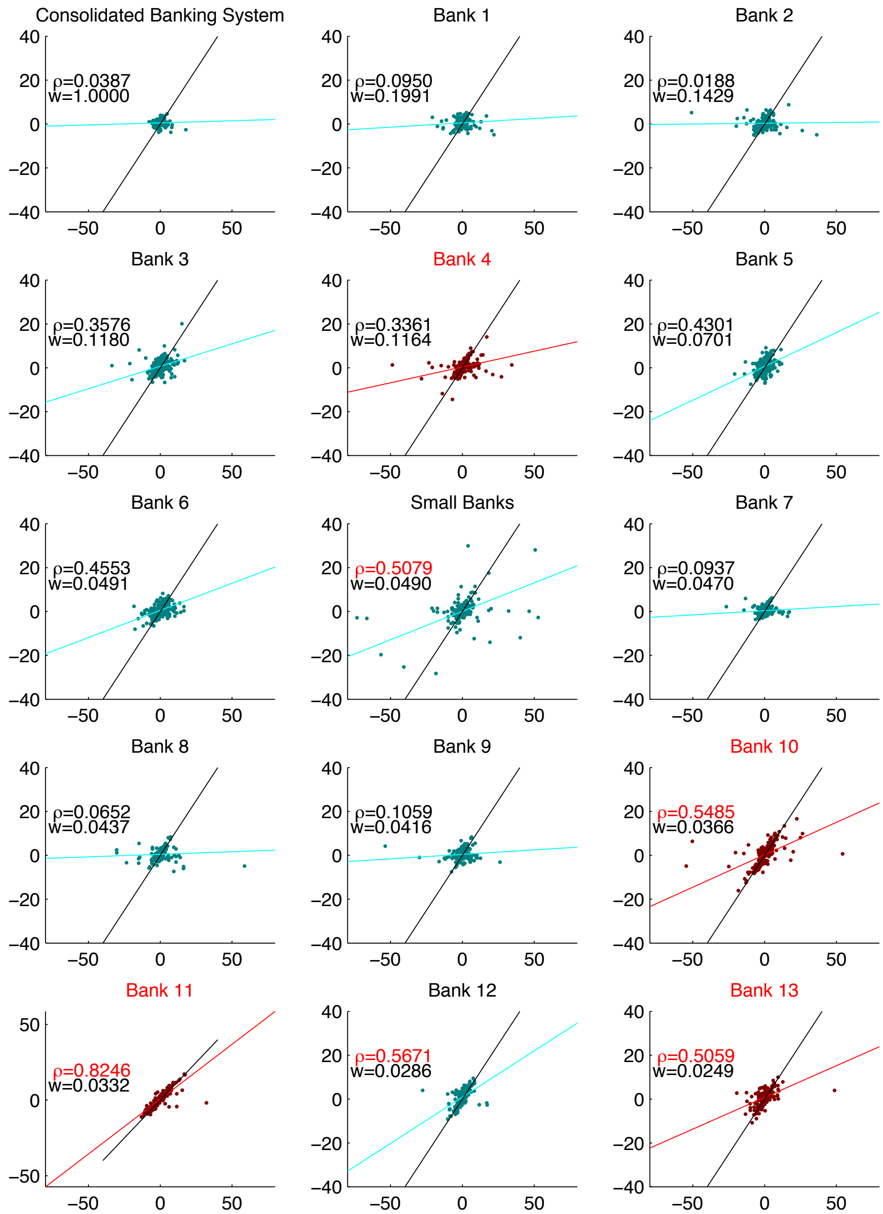
leverage growth of bank i, g_l^i is (approximately)

$$g_{it}^l = g_{it}^a - g_{it}^e$$

where $g_{it}^a = \log a_{it} - \log a_{i,t-1}$ and $g_{it}^e = \log e_{it} - \log e_{i,t-1}$.

If equity is sticky (or fixed) for whatever reason, $g_{it}^e = 0$ and changes in the size of the balance sheet of the bank will reflect leverage growth. A key feature of the banking sector is that assets are pro-cyclical (grow fast in booms and grow less or decrease in recessions) and their variation over the business cycle reflect not only better perspectives of positive net present value projects but also shifts in the banks willingness to take on risky positions. Figure 4 is replicated from Adrian and Shin [2011] using our database. It shows a scatter of the monthly changes in assets against the monthly change of leverage for the consolidated bank system and the 14 banks in our sample. The black line shows a 45 degree line, representing the case when $g_{it}^e = 0$. Points above this line indicate that during those periods equity was increasing, while the opposite happens for points below it. The blue dots correspond to a national bank while the reds to a foreign one. The variable ω shows the bank's share in total assets while ρ represents the simple correlation.

Figure 4: Leverage (X-Axis) and Assets (Y-Axis) Growth across Colombian Banks, (1994,2):(2012:4)



Note: Monthly growth rates are calculated as a log-difference, and reported in percentages. w's reported are calculated as a mean for the period (1995,12):(2000,12), and (2005,07):(2010,07). Foreign banks are displayed in red, as well as correlation coefficients greater than 0.5. Black lines in each plot are the 45 degree lines.

Based on these results, it is possible to identify two patterns of bank behavior depending on the relationship between leverage and assets or balance sheet size:

- Banks that seem to target a constant leverage ratio, $g_i^l = 0$, and display low correlation between changes in leverage and changes in total assets.
- Banks that exhibit pro-cyclical leverage or a positive relationship between changes in leverage and changes in total assets.

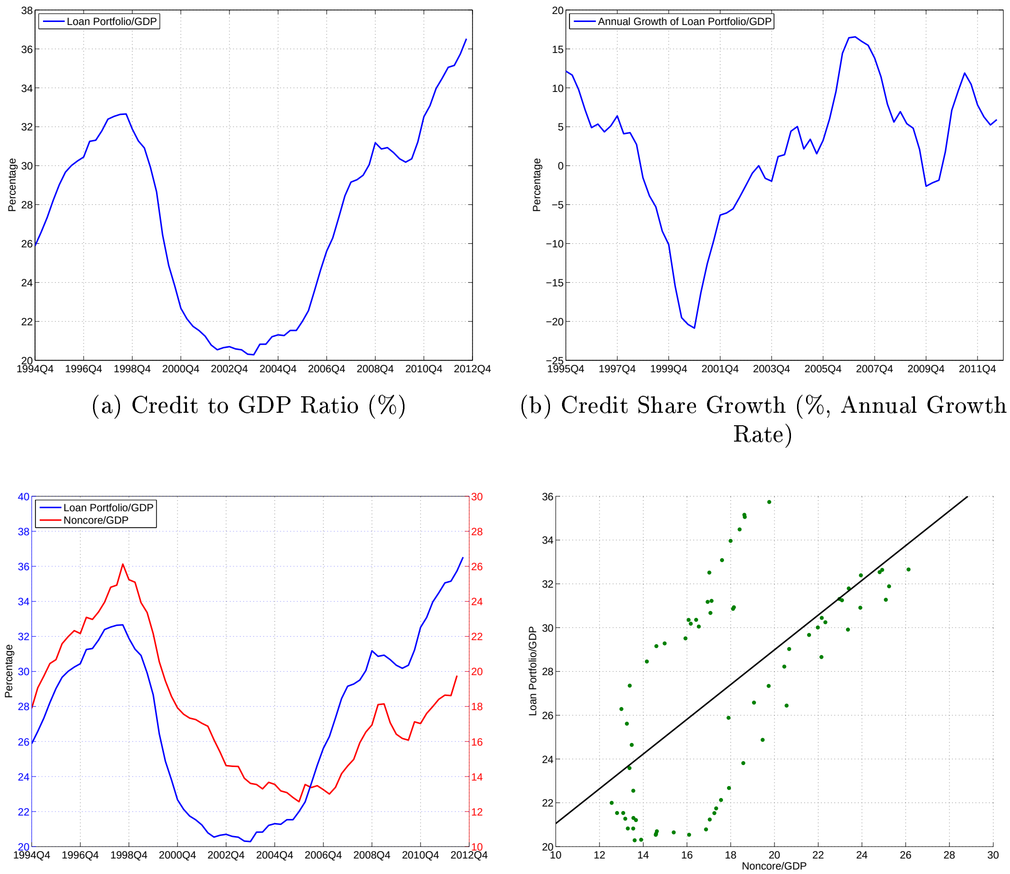
As mentioned earlier, this heterogeneity in balance sheet management practices has been linked in the literature to the degree of reliance on the capital market and mark-to-market practices. Pro-cyclical leverage might have more incidence in market-based than in bank-based credit systems [see Damar et al. [2012] for Canada and Adrian and Shin [2008] for the USA]. In Colombia, with a credit-system centered in banks, bank heterogeneity, as defined above, could be explained from differential access to markets for funding (explained by bank size or nationality, for example). We explore this issue in more detail in the next section, when we describe the econometric model.

Before moving on, there is another perspective about the fluctuations of leverage across the business cycle and its relationship with bank balance sheet. During booms, leverage capacity increases not only due to the greater profitability of bank capital but also because measured risk (for each unit of capital) falls. As Adrian and Shin [2011] point out, a higher "balance sheet capacity" translates in a higher credit supply, which needs to be funded. Thus, banks need to increase their liabilities. Since core deposits are usually long-term and stable sources of funding which change at a lower frequency than that of the business cycle, intermediaries tap other financing windows (i.e. non-core liabilities). Therefore, non-core liabilities should grow more rapidly than core liabilities.

Figures 5 and 6 present the evolution of aggregate credit and non-core liabilities in Colombia for the period 1994-2012. Here, we use our measure of non-core liabilities at the aggregate level that includes, as discussed earlier, liabilities denominated in foreign currency and CDT and bonds in domestic currency. Panel (a) of Figure 5 shows the evolution of credit as a share of GDP from 1994 to 2012. While, panel (c) adds to the previous one the share of non-core liabilities to GDP, panel (b) shows the annual growth rate of the credit-to-GDP ratio. Panel (d) is a scatter plot of credit against non-core liabilities, both as shares in GDP. In figure 6 we document the association between credit and non-core liabilities using alternative measures, mainly growth rates of these ratios.

The results point in the direction that there is a positive relationship between the level and the growth rates of credit and of non-core liabilities. The relationship remains strongly positive even when measured as a share of GDP or in growth rates of the variables of interest.

Figure 5: Evolution of Credit and Liabilities Composition (Core and Noncore) in Colombia



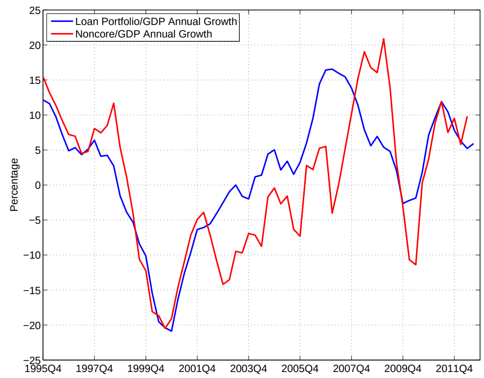
(a) Credit to GDP Ratio (%)

(b) Credit Share Growth (%, Annual Growth Rate)

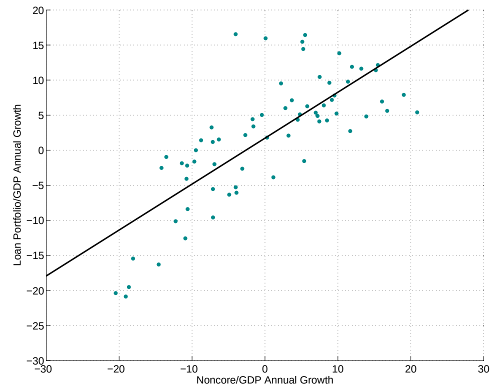
(c) Credit to GDP and Non-Core Liabilities to GDP Ratios (%)

(d) Credit to GDP vs. Non-Core Liabilities to GDP (%)

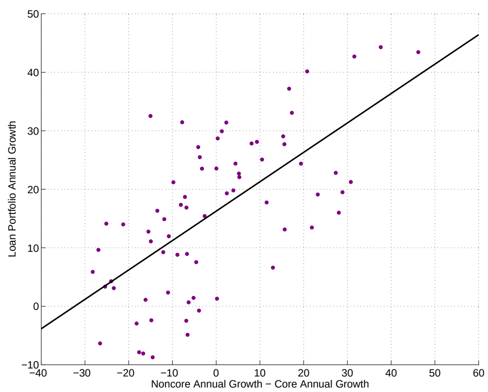
Figure 6: (Continued) Evolution of Credit and Liabilities Composition (Core and Noncore) in Colombia



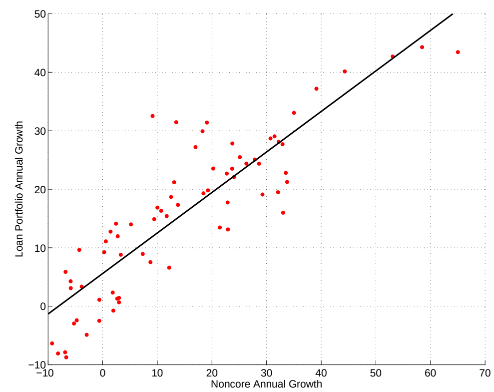
(a) Credit Share Growth and NC Liabilities Share (%, Annual Growth Rates)



(b) Credit to GDP vs. Non-Core Liabilities to GDP (Annual Growth Rates)



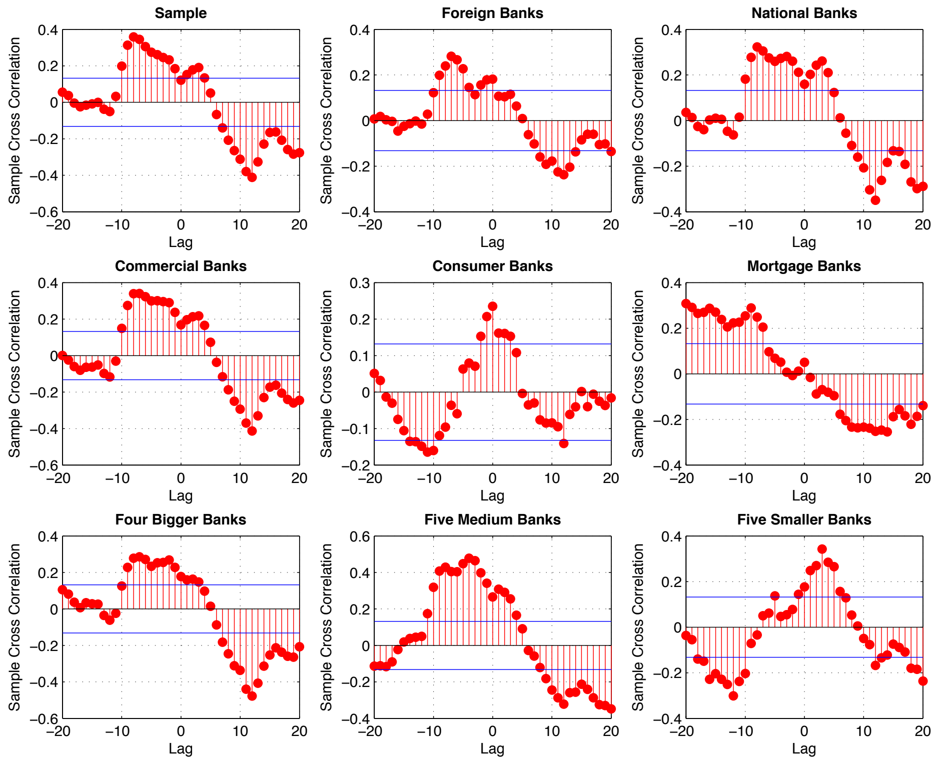
(c) Credit vs. Non-Core to Core Liabilities (Annual Growth Rates)



(d) Credit vs. Non-Core Liabilities (Annual Growth Rates)

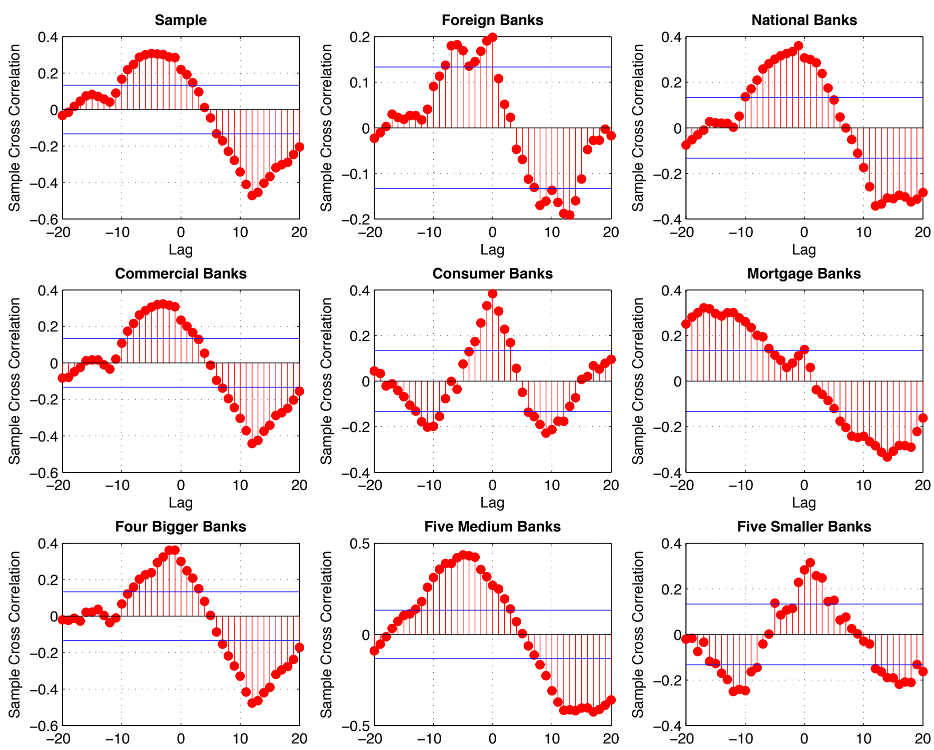
A quick inspection of these figures lead us to the observation that credit and non-core liabilities have a strong association during the different phases of the credit cycle. We can see more clearly the dynamic association between these variables if we use cross-correlograms. Figures 7 and 8 show the cross-correlograms between the ratio of non-core to core liabilities and the growth rate of total assets (Figure 7), as well as the growth rate of credit (Figure 8). Values to the right of zero in the correlograms correspond to the lags, while those to the left correspond to the leads. We compute these cross-correlograms for the aggregate sample of banks and classifying them by nationality, predominant business segment and size.

Figure 7: Cross-Correlogram of NC2C Ratio and Assets across Different Types of Banks



Note: Both series where filtered using a Hodrick-Prescott filter. Results correspond to the period (1994,1):(2012,4).

Figure 8: Cross-Correlogram of NC2C Ratio and Credit Denominated in All Currencies across Different Types of Banks



Note: Both series where filtered using a Hodrick-Prescott filter. Results correspond to the period (1994,1):(2011,12).

From these figures we highlight the following facts concerning the dynamic behavior of non-core liabilities along the credit cycle:

- There is a positive correlation between lagged non-core to core liabilities and total assets growth, for the aggregate full sample, as well as for foreign and national banks. Non-core liabilities expand in tandem with assets.
- There is a positive correlation between total asset growth and non-core to core liabilities ratio several months ahead. That is, faster credit growth today is not only associated with a contemporary expansion in the composition of banks liabilities, but also with future expansions that tend to persist for several months ahead.
- Furthermore, higher credit growth periods are anticipated by low non-core to core liabilities ratios in a monthly window of six to 20 months, depending on the type of banks. The negative correlation lags go back up to ten months for commercial banks and even longer than 20 months for mortgage banks. Consumer-credit-oriented banks display no lag.
- These patterns are stronger for large and medium-sized banks. Smaller banks exhibit a different pattern.

All our previous analysis describes plain empirical regularities. In the next section, we aim to formalize these findings through an econometric credit supply model.

3 Econometric Model

To investigate formally the relationship between credit supply and balance sheet management, we estimate the following regression:

$$g^a_{it} = \nu_i + \alpha g^l_{it} + \beta n_{it} + \delta x_{it} + \gamma z_t + \epsilon_{it} \tag{1}$$

where i indexes banks and t indexes time (in months), n_{it} is the ratio of core to non-core liabilities, x^i_t is a vector of characteristics of each bank, like size and nationality, and z_t is a vector of macroeconomic variables, such as economic activity and the monetary policy stance, which affect jointly all banks considered in our sample.

The dependent variable for the asset side of the bank can be either total assets or total outstanding loans. Total assets include total loans and banks' bond holdings, both public and private.

Alternatively, instead of considering the variables' real growth rates we also estimate a similar model but using the cyclical component of credit and leverage. More specifically, we also estimate this regression:

$$\hat{a}_{it} = \nu_i + \alpha \hat{l}_{it} + \beta n_{it} + \delta x_{it} + \gamma z_t + \epsilon_{it} \tag{2}$$

where a_{it} denotes either assets or loans of bank i at month t, the "hats" denote the deviation from trend of the variables and, as in previous specification, x^i_t is a vector of characteristics of each bank and z_t a vector of macroeconomic variables. This means that we end up with four equations to estimate.[4]

[4]This is without taking into account the possible combinations derived from all the alternative proxies we used for the left hand side variables, which served us to assess the robustness of the results.

The focus of our analysis are the parameters α and β, which we expect to be positive if the prevailing pattern in the Colombian banking industry is the "balance-sheet capacity" story. Credit supply increases with leverage ($\alpha > 0$) when banks' equity is sticky and they face other frictions (a VaR constraint, for instance) such that liabilities increase, especially non-core ones ($\beta > 0$).

We control for several factors that may affect our estimation of credit supply and use several bank-specific variables as well as macroeconomic variables. Vector x includes the following variables:

- Size: we measure size as the share of the bank's i assets in the total assets of the sample. Ex-ante, we have few strong reasons to believe that a bank's size would impact credit supply growth either positively or negatively. True, a large bank may have greater access to international financial markets than smaller banks, but the latter may also have other advantages like, in the case of Colombia, access to central bank liquidity funding facilities in the same conditions as large banks. This possibility gives them access to alternative sources of funding and so levels the playing field. In other words, we have no particular expectations about the sign of the estimated parameter for this variable.

- Nationality: A foreign bank is defined as having at least 51% of its capital owned by non-residents, like Citibank Colombia or BBVA Colombia. Differentiating banks by nationality may be important because foreign banks may have different technologies for intermediating funds between economic agents, and different risk policies and management practices in general. A foreign bank, for instance, may have access to international credit lines that other banks do not have. Alternatively, a foreign financial crisis may hit foreign banks more heavily than national ones. Therefore, foreign banks may have a wider spectrum of sources of funding than local ones. We therefore expect this variable to have a positive sign.

- Credit quality: the central bank's department of financial stability provided us a loan portfolio quality indicator (IC, *indicador de calidad de la cartera*), measured as the ratio between the risky loan portfolio and the gross loan portfolio (both without leasing), and also short-term liabilities as a share of total liabilities. Short-term liabilities include savings accounts, current account deposits, less than one-year term deposits (CDT), and interbank funds. Both series are monthly, and while IC goes from January 2002 to September 2012, the short-term liabilities indicator is available from June 1990 to September 2012. The inclusion of credit quality is a key control mechanism because it may influence banks' balance sheet management and therefore, weaken our findings. For instance, a bank could experiment idiosyncratic changes in the quality of its loan portfolio, leading it to adjust its balance sheet also idiosyncratically. A bank's credit quality may improve, freeing up space for further leverage and triggering the described mechanism. Including credit quality may alleviate this potential problem.

In vector z of macroeconomic variables we included:

- Economic activity. We considered two indicators of economic activity separately: an industrial production index and a leading indicator of Colombian GDP, IMACO. We get the IPI (Industrial Production Index), including coffee threshing, from the website of DANE[5], and seasonally adjusted it using an *x12* filter in Matlab. IMACO is a a five-month leading indicator of economic activity

[5] National Department of Statistics of Colombia

calculated monthly by the Banco de la República following the methodology described in Kamil et al. [2010]. This series is available for the full period of study. The fact that the IMACO is a leading indicator of economic activity is, in our view, an advantage as it allows us to take into consideration potential forward-looking effects in the allocation of credit.

- An indicator of the monetary policy stance. We use the interbank interest rate (TIB) to proxy for the stance of monetary policy. This is probably a good proxy since 2000 onwards, but probably not the best indicator before that year. As we explain next, we control for this possibility using a monetary policy regime dummy. The interbank rate is available only from April 1995.
- An indicator of the monetary policy regime: since our sample goes back to 1994, we acknowledge that by 1999 there was an important change in the operation of monetary policy, namely, the adoption by the central bank of an inflation targeting regime, abandoning the exchange rate crawling band system. Also, the policy instrument moved from monetary aggregates, like M1 or M3, to the short-term nominal interest rate. These changes may have had important implications for bank balance sheet management and, therefore, we set a dummy variable before and after the abandonment of the exchange rate band in September 1999.

Finally, there is a methodological point to make. We deflated, when necessary, all nominal series using the Consumer Price Index (CPI) without food, using 2008 as the base-year.

4 Estimation Results

This section discusses the main results of the estimation of equations (1) and (2). The estimation technique is OLS with fixed or random effects. To test for the reliability of the selection of fixed-effects we use the Wald test, which is an heteroskedastic and cluster-robust extension of the usual Hausman test. Table 2 reports the results of the estimation of the supply of total assets and table 3 reports those of the supply of total outstanding loans. Both tables have four columns. The first two columns correspond to the model in growth rates, equation (1), while the remaining two correspond to the model in cyclical terms, equation (2). The difference between two columns in each group is the sample period. The first corresponds to the complete period, from 1994 to 2012, while the second correspond to the period for which the credit quality index data are available.

Table 2: Detailed Regression Results for Assets Equations with Exclusion of Dependent Variable Outliers (IPI was seasonally adjusted)

VARIABLES	(1) Δln(Assets)	(2) Δln(Assets)	(3) CycleAssets	(4) CycleAssets
Δln(lev)	0.100**	0.233***		
	(0.039)	(0.053)		
Δln(lev)*Foreign	0.095	-0.043		
	(0.076)	(0.079)		
CycleLev			0.074***	0.127**
			(0.023)	(0.051)
CycleLev*Foreign			0.235***	0.116*
			(0.050)	(0.061)
NC2C	0.014***	0.009*	0.028***	0.033***
	(0.002)	(0.004)	(0.008)	(0.010)
$NC2C_{-6}$	-0.023***	-0.014***	-0.013	-0.012
	(0.003)	(0.003)	(0.009)	(0.010)
Size	0.005**	0.013	0.041***	0.080**
	(0.002)	(0.010)	(0.009)	(0.031)
(IC)		-0.005***		-0.004
		(0.001)		(0.007)
$\Delta\ln(IPI)_{-1}$	-0.001	0.013		
	(0.018)	(0.019)		
$\Delta\ln(IPI)_{-2}$	0.009	0.014		
	(0.016)	(0.018)		
$CycleIPI_{-1}$			0.076**	-0.019
			(0.025)	(0.033)
TIB_{-1}	-0.016	0.014	0.153***	0.129
	(0.013)	(0.048)	(0.035)	(0.110)
IT	0.000		0.006**	
	(0.002)		(0.003)	
Constant	0.019***	0.033	0.111***	0.223**
	(0.005)	(0.029)	(0.028)	(0.089)
Bank-specific effects	Fixed	Fixed	Fixed	Fixed
Observations	2,072	1,162	2,058	1,246
R-squared	0.131	0.195	0.220	0.237
Number of banks	14	14	14	14

Note: Arbitrary serial correlation and heteroscedasticity-robust standard errors are reported. *** p<0.01, ** p<0.05, * p<0.1. Choice for fixed-effects specifications were confirmed by a Wald test, which is an heteroskedastic and cluster-robust extension of the usual Hausman test.

Table 3: Detailed Regression Results for Credit Supply with Exclusion of Dependent Variable Outliers (IPI was seasonally adjusted)

VARIABLES	(1) Δln(Credit)	(2) Δln(Credit)	(3) CycleCredit	(4) CycleCredit
Δln(lev)	0.031*	0.067***		
	(0.017)	(0.025)		
Δln(lev)*Foreign	0.168**	0.220***		
	(0.075)	(0.074)		
CycleLev			0.050	0.074
			(0.030)	(0.045)
CycleLev*Foreign			0.145***	0.128**
			(0.046)	(0.053)
NC2C	0.013***	0.015***	0.029***	0.034***
	(0.004)	(0.005)	(0.009)	(0.010)
NC2C_{-4}	-0.021***	-0.015***	-0.011	-0.009
	(0.005)	(0.004)	(0.009)	(0.011)
Size	0.001	0.001	0.034***	0.057**
	(0.002)	(0.001)	(0.008)	(0.020)
(IC)		-0.005***		-0.009
		(0.001)		(0.007)
$\Delta\ln(\text{IPI})_{-1}$	0.012	0.048		
	(0.021)	(0.035)		
$\Delta\ln(\text{IPI})_{-2}$	0.010	0.013		
	(0.019)	(0.031)		
CycleIPI_{-1}			0.075*	-0.007
			(0.037)	(0.047)
TIB_{-1}	-0.001	-0.011	0.176***	0.240*
	(0.016)	(0.042)	(0.040)	(0.112)
IT	-0.005**		0.006*	
	(0.002)		(0.003)	
Constant	0.017**	0.002	0.091***	0.142**
	(0.007)	(0.003)	(0.025)	(0.055)
Bank-specific effects	Fixed	Random	Fixed	Fixed
Observations	2,072	1,148	2,086	1,302
R-squared	0.085	0.1364	0.166	0.191
Number of banks	14	14	14	14

Note: Arbitrary serial correlation and heteroscedasticity-robust standard errors are reported. *** p<0.01, ** p<0.05, * p<0.1. Choice for either fixed-effects or random-effects specifications were confirmed by a Wald test, which is an heteroskedastic and cluster-robust extension of the usual Hausman test.

Results from both regression models give us stronger insights on how banks manage their balance sheet. There is a strong and positive relationship between leverage and the asset side of banks' balance sheet. First, faster leverage growth translates into faster bank asset and loan growth. Second, unusually higher leverage is associated with unusually high bank assets but not with unusually high loans. At first sight, the estimated elasticities appear low but this may be misleading. Consider the first estimation of the model in growth terms. The estimated value of α ranges between 0.1 and 0.2, which means that one additional percentage point of monthly leverage growth translates into an additional 10 to 20 basis points of monthly asset growth. In annual terms, this would be about 1.2 to 2.4 percentage points larger.

Our interpretation of these results is that they support the idea that banks behave as if they maximized profits subject to a value-at-risk constraint. This means that Colombian banks may be facing funding restrictions that condition their borrowing to a risk-based capital constraint. In Colombia the solvency ratio has been around 14% on average in the last ten years. Although this constraint may not be binding at all times, it may affect lending supply dynamics. Given that banks' ability to lend is determined by risk-management practices and regulatory considerations, when risk perceptions and or measures improve, banks expand their lending so as to make full use of their lending capacity. Thus, assets grow and leverage increases.

The results of the estimation of parameter β add further support to this view. There is a strong and positive relationship between the composition of liabilities and the asset side of banks' balance sheet. First, a larger share of non-core liabilities translates into faster bank assets and loans growth. Second, an unusually large share of noncore liabilities is associated with unusually high bank assets and loans. The quantitative results here are harder to interpret because in this case the estimated parameter is a semi-elasticity. Nonetheless, it is quite clear from the estimations that this relation is robust for all model specifications. Our interpretation is that the expansion of balance sheets, driven by the need to use up the already described mechanism of enlarged lending capacity, leads banks to resort to alternative means of funding other than their usual core liabilities. This is so because of the intrinsic properties of these liabilities, as they respond more to low frequency movements than to cyclically high frequency changes of the funding needs of banks. Therefore, both of our findings lead us to believe that the size of the balance sheet (either credit or total assets), leverage and the composition of bank liabilities are part of the same process, lending support to a model in which banking frictions are relevant.

These results may be questioned from several dimensions, several of which we tackle in the following paragraphs. A first line of criticism may be related to the quality of our proxies. It may be argued that industrial production is probably not the best indicator of economic activity. In order to respond to this argumernt we consider using the IMACO, a leading indicator of GDP growth, as an alternative proxy in the regression model. Table 4 reports the results. The values of the estimated parameters are similar to those obtained under the model specification which considers the industrial production index.

Table 4: Detailed Regression Results Using IMACO as Regressor, and Excluding Dependent Variable Outliers

VARIABLES	(1) Δln(Assets)	(2) Δln(Assets)	(3) Δln(Credit)	(4) Δln(Credit)t
Δ ln(lev)	0.100**	0.233***	0.033*	0.067**
	(0.040)	(0.053)	(0.017)	(0.025)
Δ ln(lev)*Foreign	0.096	-0.043	0.167**	0.215**
	(0.075)	(0.080)	(0.074)	(0.071)
NC2C	0.013***	0.010**	0.012**	0.014**
	(0.002)	(0.005)	(0.004)	(0.007)
$NC2C_{-4}$			-0.016***	-0.016***
			(0.005)	(0.004)
$NC2C_{-6}$	-0.020***	-0.013***		
	(0.003)	(0.003)		
(IC)		-0.005***		-0.004*
		(0.001)		(0.002)
Size	0.005**	0.013	0.001	0.004
	(0.002)	(0.010)	(0.002)	(0.006)
IMACO	0.079***	0.051	0.165***	0.144*
	(0.021)	(0.033)	(0.035)	(0.068)
TIB_{-1}	-0.029**	-0.005	-0.026*	-0.080*
	(0.012)	(0.045)	(0.015)	(0.041)
IT	-0.001		-0.009***	
	(0.002)		(0.002)	
Constant	0.019***	0.033	0.017**	0.007
	(0.005)	(0.029)	(0.007)	(0.017)
Bank-specific effects	Fixed	Fixed	Fixed	Fixed
Observations	2,072	1,162	2,072	1,148
R-squared	0.134	0.195	0.099	0.140
Number of banks	14	14	14	14

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

Note: Arbitrary serial correlation and heteroscedasticity-robust standard errors are reported. *** p<0.01, ** p<0.05, * p<0.1. Choice for fixed-effects specifications were confirmed by a Wald test, which is an heteroskedastic and cluster-robust extension of the usual Hausman test.

A second dimension along which our results may be questioned is the estimation technique. There are at least two potential problems here: the presence of outliers and the potential endogeneity of leverage and of the non-core to core liabilities ratio. To prevent the effects of outliers, Tables 2 to 4 show the results from the fixed-effects specifications excluding the dependent variable observations in the 1st and 99th percentiles. We also checked that excluded outliers did not come from the same bank (or few banks) and were not concentrated in certain years of the sample. Nonetheless, we also report in the appendix the results without eliminating the outliers (see Tables A.1 to A.3).

There is a potential endogeneity between credit supply growth, leverage and non-core to core liabilities. The reader may wonder why we did not estimate the model by GMM and used lagged non-core to core liabilities ratio as instrument, which is frequently used practice in the literature of monetary policy transmission mechanisms (see, for example, Akbostanci and Ozsuca [2012]). However, the properties of our sample are not suitable for this technique. In the database, time series realizations are much larger than cross-section observations, $T > N$. N is only 14 while T ranges between 82 and 148, depending of whether we include the credit quality index or not. Thus for GMM estimation there will be a very large number of moment conditions, making the computational problem intractable. Furthermore, as discussed in Baltagi [2005], when T is too large the downward bias of GMM is quite severe, outweighing the potential gains in efficiency. We deal with this problem using lags of non-core to core liabilities as well as leverage.[6]

A third possible criticism is that results may be driven by monetary policy or economic fluctuations. Changes in the policy rate may explain the described dynamics of credit, leverage and non-core liabilities. A similar argument applies to the phase of the business cycle. During expansions it is expected that credit grows, leverage increases and demand for alternative bank liabilities to flourishes. To deal with this problem, we included the interbank interest rate as a proxy of the stance of monetary policy and the industrial production index as a proxy of monthly economic activity (see Tables A.4 to A.6) since there is no monthly measure of GDP in Colombia.

The results of our baseline regressions show that the effect of the policy rate (TIB) on the dynamics of both growth and credit is not robust to alternative specifications. On the one hand, the results displayed in Table 4, with the leading economic activity index (IMACO) instead of the industrial production index (IPI) as an explanatory variable, are in line with the empirical literature on the risk-taking channel. This literature argues that lower interest rates increase banks' willingness to take risks, thus increasing leverage, and leading to faster growth of credit and assets. On the other hand, in Tables 2 and 3, three out of 8 specifications showed that increases in the short-term interest rate coincide with the expansionary phase of the credit and assets cycles.

A possible explanation for the weakness of this parameter may be that the policy rate may be endogenous to credit growth, a problem that our empirical methodology cannot fully account for. We doubt that this is case. In the estimated regression, the dependent variable is the credit growth of a particular bank i, not *aggregate* credit. Circumstantial evidence allows us to contend, quite confidently, that the central bank does not set the intervention rate by targeting credit growth of a particular bank. Of course, it is possible that aggregate credit may influence the determination of TIB, but this is not how ours models are specified.

Another possibility is that monetary policy affects credit with long lags, and not only through changes in the level of the interest rate but through deviations from a "neutral rate". Thus, we use multiple lags of the policy rate and run the same regressions as in Tables 2 to 4 but using the difference between the policy rate and its long run value, calculated by means of a Hodrick-Prescott filter. By removing the long-run component of the policy rate, we are also reducing the likelihood that this variable is stationary. This is certainly another source of the potential lack of robustness of that estimated parameter. Tables A.4 to A.6 show the results of these estimations, each one reporting the lags of our fairly exogenous measure of monetary policy, that are found to be negative and highly significant.[7]

Finally, one may argue that the regressions that include the leading economic activity index as a regressor can account, at least partially, for the preemptive counter-cyclical policy actions of the central bank. These actions may be behind the positive coefficient reported in Tables 2 and 3. For instance, when the bank expects a slowdown of the economy and cuts the interest rates, it is unlikely that it can increase

[6] Most of these regressions are reported in the appendix titled "Robustness of the results". The other are available upon request.

[7] We also included simultaneously the 24 lags of CycleTIB in our regressions, as in Romer and Romer [2004], who found that a contractionary monetary shock negatively impacts industrial production between months 5 and 24. We were, however, expecting a faster effect of monetary policy on banks' credit supply and assets. In these regressions, most of the lags were negative, but few of them individually significant. Results of these regressions are available upon request.

output (although it can make the fall of output less sharp). As a leading index that groups a significant amount of information regarding the future development of the economy, the leading economic activity index may be successful in purging our monetary policy measure from counter-cyclical policy actions taken in anticipation of future booms and recessions. The control mechanism may be similar to the one used in VAR's literature of applied international macroeconomics, where controlling for commodities prices largely eliminates the 'price puzzle', that is, the fact that the price level increases in the first months after an increase in the interest rates.

In sum, we perform several robustness checks and report them in the appendix. There, the reader can check that the sign and values of the estimated parameters α and β. In our judgment the estimation results remain robust to a wide range of alternative specifications.

5 Conclusions

The findings obtained in this paper make it possible to approach credit dynamics from a wider perspective that includes both sides of bank's balance sheet and that also sheds light into the links that exist, at an aggregate level, between monetary variables and credit.

These results clearly indicate that there is an interesting connection in Colombia between bank credit/asset growth, liability composition and leverage. This means that, despite the characteristics of the banking system in the country, banks seem to manage their balance sheet according to a model of credit in which risk perceptions and funding restrictions are important.

In terms of balance sheet management in general, and credit supply decisions in particular, the banking sector in Colombia is predominantly pro-cyclical, which has important implications for the analysis of the relationship between financial and business cycles, the amplification of shocks and the way financial imbalances incubate in the economy.

The composition of bank liabilities between core and non-core, as defined in this paper, provides important information for policy makers regarding the phase of the cycle of the economy. Foreign-denominated liabilities of banks, although they represent a relatively small share of non-core liabilities in Colombia, are particularly dynamic during the upward phase of the leverage cycle. Taking this into account, a shift from core to non-core liabilities could play the role of an early warning indicator of financial vulnerability. Periods in which banks shift from lower to higher non-core liability ratios may signal the beginning of credit cycles.

The contention that banks manage their balance sheet in a pro-cyclical fashion is consistent with the apparent stability of the average leverage ratio of the banking sector in Colombia. Leverage ratios of individual banks display a wide dispersion and also vary in the different phases of the cycle of the economy.

Bank heterogeneity matters when studying how banks manage their balance sheet. In particular, foreign banks exhibit higher leverage and non-core to core liabilities ratios than local banks. Mortgage banks are more leveraged than other banks. Consumer banks have the highest non-core to core liability ratio of the sample. Not always conclusively, bank size tends to be positively correlated with balance and credit growth. Most significantly, foreign banks display the highest degree of pro-cyclicality.

These results point in the direction of the need to revise the traditional analyzes of changes in monetary variables in terms of shifts in the demand for money, for example between liquid less liquid assets. The hypothesis tested in this work, that credit supply decisions by banks are better understood as part of how they manage their balance sheets, illustrate that causation might very well go from credit to money.

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A Robustness Checks

Table A.1: Detailed Regression Results for Assets Equation (IPI was seasonally adjusted)

VARIABLES	(1) $\Delta\ln$(Assets)	(2) $\Delta\ln$(Assets)	(3) $\Delta\ln$(Assets)	(4) $\Delta\ln$(Assets)	(5) CycleAssets	(6) CycleAssets	(7) CycleAssets	(8) CycleAssets
$\Delta\ln$(lev)	0.178***	0.178***	0.346***	0.349***				
	(0.047)	(0.047)	(0.094)	(0.095)				
$\Delta\ln$(lev)*Foreign	0.145	0.147	-0.013	-0.011				
	(0.101)	(0.101)	(0.129)	(0.130)				
CycleLev					0.131**	0.137***	0.175**	0.181**
					(0.045)	(0.045)	(0.078)	(0.091)
CycleLev*Foreign					0.229***	0.244***	0.139	0.177*
					(0.073)	(0.078)	(0.097)	(0.105)
NC2C	0.011***	0.016***	0.005	0.010***	0.030**	0.028**	0.030**	0.030**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.011)	(0.011)	(0.012)	(0.013)
NC2C$_{-6}$	-0.021***	-0.018***	-0.014***	-0.009**	-0.017	-0.019*	-0.018	-0.022*
	(0.004)	(0.004)	(0.005)	(0.004)	(0.011)	(0.011)	(0.013)	(0.012)
Size	0.007***	0.000	0.024*	0.002*	0.050***	0.008***	0.112**	0.007***
	(0.002)	(0.001)	(0.013)	(0.001)	(0.011)	(0.003)	(0.045)	(0.003)
(IC)			-0.003	-0.005***			-0.001	-0.004
			(0.002)	(0.001)			(0.009)	(0.003)
Foreign		0.001		-0.003**		-0.000		-0.005**
		(0.002)		(0.002)		(0.002)		(0.002)
$\Delta\ln$(IPI)$_{-1}$	0.023	0.029	0.011	0.017				
	(0.024)	(0.024)	(0.027)	(0.026)				
$\Delta\ln$(IPI)$_{-2}$	0.017	0.023	-0.006	-0.001				
	(0.021)	(0.023)	(0.024)	(0.023)				
CycleIPI$_{-1}$					0.032	0.025	-0.033	-0.044
					(0.036)	(0.040)	(0.050)	(0.057)
TIB$_{-1}$	-0.009	-0.012	0.006	0.029	0.225***	0.234***	0.249*	0.219*
	(0.020)	(0.020)	(0.065)	(0.064)	(0.049)	(0.052)	(0.130)	(0.130)
IT	0.003	0.007***			0.008**	0.007***		
	(0.002)	(0.002)			(0.003)	(0.002)		
Constant	0.024***	0.001	0.067	0.001	0.134***	0.012	0.317**	0.010
	(0.007)	(0.002)	(0.039)	(0.004)	(0.031)	(0.008)	(0.130)	(0.010)
Bank-specific effects	Fixed	Random	Fixed	Random	Fixed	Random	Fixed	Random
Observations	2,800	2,800	1,680	1,680	2,800	2,800	1,680	1,680
R-squared	0.224	0.218	0.337	0.330	0.261	0.2262	0.317	0.2242
Number of banks	14	14	14	14	14	14	14	14

Note: All variables in cycles were calculated using a Hodrick-Prescott filter. Arbitrary serial correlation and heteroscedasticity-robust standard errors are reported.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Choice for fixed-effects specifications were confirmed by a Wald test, which is an heteroskedastic and cluster-robust extension of the usual Hausman test.

Table A.2: Detailed Regression Results for Credit Supply (IPI was seasonally adjusted)

VARIABLES	(1) Δln(Credit)	(2) Δln(Credit)	(3) Δln(Credit)	(4) Δln(Credit)	(5) CycleCredit	(6) CycleCredit	(7) CycleCredit	(8) CycleCredit
Δln(lev)	0.055**	0.055***	0.094***	0.095***				
	(0.018)	(0.018)	(0.022)	(0.022)				
Δln(lev)*Foreign	0.179***	0.180***	0.151**	0.151**				
	(0.047)	(0.047)	(0.060)	(0.060)				
CycleLev					0.053**	0.059***	0.058	0.064
					(0.022)	(0.021)	(0.048)	(0.052)
CycleLev*Foreign					0.186***	0.200***	0.160**	0.188***
					(0.046)	(0.050)	(0.059)	(0.066)
NC2C	0.022***	0.025***	0.019**	0.022***	0.047***	0.042***	0.053***	0.046***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.013)	(0.014)	(0.014)	(0.014)
$NC2C_{-4}$	-0.029***	-0.027***	-0.024***	-0.021***	-0.027*	-0.031**	-0.027*	-0.037***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.014)	(0.013)	(0.015)	(0.013)
Size	0.003	-0.001	0.005	0.000	0.044***	0.008***	0.080***	0.006**
	(0.002)	(0.001)	(0.007)	(0.001)	(0.011)	(0.003)	(0.025)	(0.003)
(IC)			-0.004**	-0.006***			-0.009	-0.007**
			(0.002)	(0.001)			(0.008)	(0.003)
Foreign		-0.001		-0.004**		-0.001		-0.008***
		(0.002)		(0.002)		(0.002)		(0.003)
$\Delta\ln(IPI)_{-1}$	0.027	0.031	0.051*	0.054**				
	(0.024)	(0.023)	(0.025)	(0.025)				
$\Delta\ln(IPI)_{-2}$	0.026	0.030*	0.019	0.021				
	(0.017)	(0.017)	(0.019)	(0.018)				
$CycleIPI_{-1}$					0.035	0.026	0.012	-0.001
					(0.046)	(0.047)	(0.047)	(0.052)
TIB_{-1}	-0.003	-0.006	-0.057	-0.048	0.216***	0.230***	0.251*	0.240
	(0.023)	(0.022)	(0.045)	(0.040)	(0.058)	(0.061)	(0.122)	(0.153)
IT	-0.003	-0.001			0.011**	0.008**		
	(0.002)	(0.003)			(0.004)	(0.003)		
Constant	0.023***	0.009***	0.017	0.002	0.113***	0.012	0.209***	0.001
	(0.007)	(0.002)	(0.019)	(0.003)	(0.032)	(0.009)	(0.069)	(0.009)
Bank-specific effects	Fixed	Random	Fixed	Random	Fixed	Random	Fixed	Random
Observations	2,800	2,800	1,680	1,680	2,800	2,800	1,680	1,680
R-squared	0.118	0.115	0.144	0.143	0.187	0.158	0.235	0.168
Number of banks	14	14	14	14	14	14	14	14

Note: All variables in cycles were calculated using a Hodrick-Prescott filter. Arbitrary serial correlation and heteroscedasticity-robust standard errors are reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Choice for fixed-effects specifications were confirmed by a Wald test, which is an heteroskedastic and cluster-robust extension of the usual Hausman test.

Table A.3: Detailed Regression Results Using IMACO as Regressor

VARIABLES	(1) Δln(Assets)	(2) Δln(Assets)	(3) Δln(Assets)	(4) Δln(Assets)	(5) Δln(Credit)	(6) Δln(Credit)	(7) Δln(Credit)	(8) Δln(Credit)
Δln(lev)	0.178***	0.178***	0.346***	0.349***	0.055***	0.056***	0.093***	0.095***
	(0.047)	(0.047)	(0.094)	(0.095)	(0.018)	(0.018)	(0.022)	(0.022)
Δln(lev)*Foreign	0.145	0.147	-0.014	-0.013	0.179***	0.179***	0.147**	0.147**
	(0.100)	(0.100)	(0.130)	(0.131)	(0.046)	(0.046)	(0.060)	(0.061)
NC2C	0.010***	0.014***	0.006	0.011***	0.021***	0.022***	0.020***	0.023***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
$NC2C_{-4}$					-0.025***	-0.023***	-0.023***	-0.021***
					(0.006)	(0.005)	(0.006)	(0.006)
$NC2C_{-6}$	-0.018***	-0.015***	-0.014**	-0.009**				
	(0.004)	(0.004)	(0.005)	(0.004)				
Size	0.008***	0.000	0.024*	0.002*	0.004	-0.001	0.006	0.001
	(0.002)	(0.001)	(0.013)	(0.001)	(0.002)	(0.001)	(0.007)	(0.001)
(IC)			-0.003	-0.005***			-0.004**	-0.005***
			(0.002)	(0.001)			(0.002)	(0.001)
Foreign		0.000		-0.003**		-0.001		-0.004**
		(0.002)		(0.001)		(0.002)		(0.002)
IMACO	0.092***	0.122***	0.045	0.072*	0.129***	0.142***	0.091*	0.113***
	(0.025)	(0.021)	(0.065)	(0.038)	(0.020)	(0.022)	(0.050)	(0.040)
TIB_{-1}	-0.028	-0.037**	-0.011	-0.004	-0.031	-0.035	-0.103**	-0.106***
	(0.018)	(0.018)	(0.059)	(0.064)	(0.022)	(0.022)	(0.040)	(0.036)
IT	0.001	0.003			-0.006***	-0.005**		
	(0.002)	(0.002)			(0.002)	(0.002)		
Constant	0.025***	0.001	0.066	0.000	0.023***	0.010***	0.016	0.000
	(0.006)	(0.002)	(0.039)	(0.004)	(0.008)	(0.002)	(0.019)	(0.003)
Bank-specific effects	Fixed	Random	Fixed	Random	Fixed	Random	Fixed	Random
Observations	2,800	2,800	1,680	1,680	2,800	2,800	1,680	1,680
R-squared	0.225	0.221	0.337	0.330	0.123	0.121	0.143	0.142
Number of banks	14	14	14	14	14	14	14	14

Note: Arbitrary serial correlation and heteroscedasticity-robust standard errors are reported. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Choice for fixed-effects specifications were confirmed by a Wald test, which is an heteroskedastic and cluster-robust extension of the usual Hausman test.

Table A.4: Detailed Regression Results for Assets Equations with Exclusion of Dependent Variable Outliers (IPI was seasonally adjusted)

VARIABLES	(1) Δln(Assets)	(2) Δln(Assets)	(3) Δln(Assets)	(4) Δln(Assets)	(5) Δln(Assets)	(6) Δln(Assets)	(7) CycleAssets	(8) CycleAssets
Δln(lev)	0.098**	0.095**	0.093**	0.231***	0.231***	0.231***		
	(0.039)	(0.038)	(0.038)	(0.053)	(0.053)	(0.052)		
Δln(lev)*Foreign	0.095	0.089	0.091	-0.043	-0.041	-0.042		
	(0.074)	(0.072)	(0.072)	(0.079)	(0.079)	(0.079)		
CycleLev							0.067***	0.129**
							(0.022)	(0.051)
CycleLev*Foreign							0.239***	0.112*
							(0.044)	(0.058)
NC2C	0.014***	0.012***	0.011***	0.009*	0.009*	0.009*	0.042***	0.033***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.007)	(0.009)
NC2C$_{-6}$	-0.023***	-0.020***	-0.020***	-0.018***	-0.017***	-0.017***	-0.021**	-0.019*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.009)	(0.011)
Size	0.004**	0.005**	0.005**	0.016	0.016	0.016	0.053***	0.083**
	(0.002)	(0.002)	(0.002)	(0.010)	(0.010)	(0.010)	(0.011)	(0.031)
Cycle(IC)				-0.005	-0.005	-0.005		-0.013
				(0.005)	(0.006)	(0.006)		(0.015)
Δln(IPI)$_{-1}$	-0.004	0.000	0.001	0.005	0.005	0.005		
	(0.018)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)		
Δln(IPI)$_{-2}$	0.001	0.011	0.010	0.007	0.007	0.007		
	(0.015)	(0.016)	(0.016)	(0.018)	(0.017)	(0.018)		
CycleIPI$_{-1}$							0.077**	-0.007
							(0.032)	(0.034)
CycleTIB$_{-4}$	-0.060***			-0.060				
	(0.018)			(0.113)				
CycleTIB$_{-13}$		-0.031**			-0.101*			
		(0.011)			(0.056)			
CycleTIB$_{-14}$			-0.052***			-0.096	-0.074*	0.114
			(0.012)			(0.068)	(0.039)	(0.246)
IT	0.002	0.002	0.001				0.006	
	(0.002)	(0.002)	(0.002)				(0.004)	
Constant	0.017***	0.018**	0.019***	0.053*	0.053*	0.053*	0.148***	0.240**
	(0.006)	(0.006)	(0.006)	(0.029)	(0.029)	(0.029)	(0.032)	(0.089)
Bank-specific effects	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Observations	2,030	1,932	1,918	1,162	1,162	1,162	1,876	1,246
R-squared	0.131	0.124	0.125	0.191	0.191	0.191	0.227	0.236
Number of banks	14	14	14	14	14	14	14	14

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

Table A.5: Detailed Regression Results for Credit Supply with Exclusion of Dependent Variable Outliers (IPI was seasonally adjusted)

VARIABLES	(1) $\Delta\ln(\text{Credit})$	(2) $\Delta\ln(\text{Credit})$	(3) $\Delta\ln(\text{Credit})$	(4) $\Delta\ln(\text{Credit})$	(5) CycleCredit	(6) CycleCredit
$\Delta\ln(\text{lev})$	0.030	0.031	0.066**	0.066**		
	(0.018)	(0.018)	(0.025)	(0.025)		
$\Delta\ln(\text{lev})$*Foreign	0.173**	0.169*	0.219**	0.219**		
	(0.080)	(0.081)	(0.074)	(0.074)		
CycleLev					0.041	0.074
					(0.029)	(0.044)
CycleLev*Foreign					0.176***	0.129**
					(0.036)	(0.050)
NC2C	0.012**	0.012**	0.011*	0.011*	0.039***	0.034***
	(0.004)	(0.004)	(0.006)	(0.006)	(0.008)	(0.008)
NC2C_{-4}	-0.019***	-0.019***	-0.019***	-0.019***	-0.023**	-0.019*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)	(0.010)
Size	0.001	0.001	0.005	0.005	0.048***	0.065***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.010)	(0.018)
Cycle(IC)			-0.009*	-0.009*		-0.011
			(0.005)	(0.005)		(0.010)
$\Delta\ln(\text{IPI})_{-1}$	0.007	0.012	0.042	0.044		
	(0.021)	(0.022)	(0.036)	(0.036)		
$\Delta\ln(\text{IPI})_{-1}$	0.006	0.015	0.007	0.008		
	(0.020)	(0.021)	(0.031)	(0.031)		
CycleIPI_{-1}					0.104**	-0.011
					(0.044)	(0.043)
CycleTIB_{-11}	-0.073***		-0.085			
	(0.015)		(0.122)			
CycleTIB_{-14}		-0.073***		-0.037		
		(0.016)		(0.099)		
CycleTIB_{-19}					-0.152***	-0.551**
					(0.049)	(0.252)
IT	-0.004*	-0.004			-0.007*	
	(0.002)	(0.003)			(0.004)	
Constant	0.017*	0.016*	0.024	0.024	0.146***	0.190***
	(0.008)	(0.009)	(0.014)	(0.014)	(0.027)	(0.050)
Bank-specific effects	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Observations	1,946	1,904	1,148	1,148	1,834	1,302
R-squared	0.092	0.087	0.137	0.137	0.195	0.184
Number of bancos	14	14	14	14	14	14

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

Table A.6: Detailed Regression Results Using IMACO as Regressor, and Excluding Dependent Variable Outliers

VARIABLES	(1) $\Delta\ln$(Assets)	(2) $\Delta\ln$(Assets)	(3) $\Delta\ln$(Assets)	(4) $\Delta\ln$(Assets)	(5) $\Delta\ln$(Credit)	(6) $\Delta\ln$(Credit)	(7) $\Delta\ln$(Credit)	(8) $\Delta\ln$(Credit)
$\Delta\ln$(lev)	0.098**	0.093**	0.231***	0.231***	0.034*	0.032*	0.067***	0.067***
	(0.039)	(0.038)	(0.053)	(0.053)	(0.017)	(0.017)	(0.026)	(0.026)
$\Delta\ln$(lev)*Foreign	0.096	0.091	-0.042	-0.042	0.165**	0.169**	0.217***	0.218***
	(0.073)	(0.071)	(0.079)	(0.079)	(0.074)	(0.076)	(0.073)	(0.073)
NC2C	0.013***	0.011***	0.010**	0.009*	0.013***	0.012**	0.016***	0.016***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
$NC2C_{-4}$					-0.016***	-0.016***	-0.015***	-0.014***
					(0.005)	(0.005)	(0.004)	(0.004)
$NC2C_{-6}$	-0.020***	-0.020***	-0.017***	-0.016***				
	(0.003)	(0.003)	(0.004)	(0.004)				
Size	0.005**	0.005**	0.016	0.016	0.002	0.001	0.001	0.001
	(0.002)	(0.002)	(0.010)	(0.010)	(0.002)	(0.003)	(0.001)	(0.001)
Cycle(IC)			-0.004	-0.004			-0.007	-0.007
			(0.005)	(0.005)			(0.005)	(0.005)
IMACO$-\Delta Y^*$	0.071***	0.017	0.060	0.038	0.193***	0.169***	0.159***	0.148**
	(0.023)	(0.022)	(0.036)	(0.041)	(0.039)	(0.038)	(0.058)	(0.060)
$CycleTIB_{-2}$					-0.072***		-0.113	
					(0.015)		(0.072)	
$CycleTIB_{-4}$	-0.067***		-0.082			-0.051**		-0.092
	(0.019)		(0.110)			(0.018)		(0.084)
$CycleTIB_{-14}$		-0.046***		-0.072				
		(0.010)		(0.070)				
IT	0.000	0.000			-0.008***	-0.008***		
	(0.002)	(0.002)			(0.002)	(0.002)		
Constant	0.019***	0.019***	0.054*	0.054*	0.023***	0.022**	0.014***	0.014***
	(0.006)	(0.006)	(0.028)	(0.028)	(0.008)	(0.008)	(0.002)	(0.002)
Bank-specific effects	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed	Random	Random
Observations	2,030	1,918	1,162	1,162	2,058	2,030	1,148	1,148
R-squared	0.133	0.125	0.191	0.191	0.105	0.102	0.136	0.136
Number of bancos	14	14	14	14	14	14	14	14

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