How do bank-specific characteristics affect lending? New evidence based on credit registry data from Latin America

Carlos Cantú¹, Stijn Claessens² and Leonardo Gambacorta³

Abstract

This paper studies the recent evolution of banking systems in Latin America and analyses how bank specific characteristics affect credit supply. We use detailed credit registry data for five countries (Brazil, Chile, Colombia, Mexico and Peru) applying a common empirical strategy to make results comparable. Data confidentiality does not allow us to pool the data so we use meta-analysis techniques to summarise the results. We find that, within banks, those with strong balance sheet characteristics (large, liquid and well-capitalised), low risk indicators, stable sources of funding, and a commercial business model supply more credit and are more sheltered against monetary and global shocks.

Keywords: bank business models, bank lending, credit registry data, meta-analysis JEL classification: E51, E58, G21

¹ Bank for International Settlements. Carlos.Cantu@bis.org.

- ² Bank for International Settlements and CEPR. Stijn.Claessens@bis.org.
- ³ Bank for International Settlements and CEPR. Leonardo Gambacorta@bis.org.

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1. Introduction

After the great financial crisis (GFC), banks' activities and business models have undergone many changes. Banks' capitalization – in level and form of capital, their funding, and what types of financial intermediation activities they engage have altered, driven in part by how banks are regulated from capital, liquidity and other perspectives. These and other changes have had profound effects on how banks grant credit and likely affected how banks react to monetary policy and external shocks. Several studies have focused on some of the changes in bank business models in advanced economies after the crisis and their effects (see, amongst others Gambacorta and Marques-Ibanez (2011), Roengpitya et al (2017), and Gambacorta et al. (2018); see CGFS (2018) for a review of changes in banking systems and their effects). Analysis on emerging markets, however, has been less.

The objective of this paper is to understand how the evolution of the banking systems of the main economies in Latin America and their peculiarities has affected the drivers of credit supply, including their responses to shocks.⁴ Lending is the most important component of banks' assets and is crucial for firms' financing, especially in emerging markets where alternative forms of (market) funding are typically quite limited. The bank lending channel literature has focused so far on how back characteristic can alter the transmission of monetary policy shocks on the supply of credit. In this paper, we analyse in a more comprehensive way the role of bank characteristics in influencing the supply of credit. In particular, we consider the direct impact of characteristics on lending supply (ie do well-capitalised banks supply more credit?) and how these characteristics affect the reaction of bank lending to shocks (ie does the lending supply of well-capitalised banks react by less to an external shock?). We analyse not only monetary policy shocks but also shocks to global liquidity or to global uncertainty.

To disentangle the effects of credit supply from those of credit demand, the paper uses analyses that employ very granular data at the bank-firm level. In particular, we use studies for five countries that use a credit registry database to analyse the effects on (changes in) bank business models on the supply of credit. As it was not possible to pool the highly confidential data in one database and run panel regression, all country teams used a common methodology to evaluate how different bank-characteristics (or business models) affect loan supply growth. We then compile the results obtained by each country and used meta-analysis techniques to summarise the findings. Beyond applying a common analytical framework, adapted in some cases to take into account specific institutional details, each country team contributed with a narrative specific to their national experience.

Our main results are the following. First, we find that, within banks, those that are large, well-capitalised, and with a commercial business model supply more credit. On the contrary, banks that have high-risk indicators, volatile sources of funding and a universal business model, other things being equal, are associated with a lower supply of loans.

⁴ This project was developed under the auspices of the Consultative Council for the Americas (CCA) Consultative Group of Directors of Financial Stability (CGDFS) and covers five countries that are BIS shareholders: Brazil, Chile, Colombia, Mexico and Peru.

Second, we find that the lending supply of well-capitalised banks is less affected by monetary policy shocks, while those with commercial business models (that rely more heavily on deposits) are more affected by monetary policy shocks.

Third, bank with different characteristics react differently to global shocks. Those with high capital, high liquidity and more stable sources of funding are less affected by high-risk shocks. Moreover, in high liquidity periods, banks that are large, more profitable and with a commercial business model reduce more their credit supply. Banks with high levels of capital and stable sources of funding are more sheltered against economic policy uncertainty shocks. Finally, banks that are large and well capitalised reduce less their credit supply when faced with a commodity price shock.

The structure of the paper is as follows. In section 2, we first review related literature. Section 3 then presents an assessment of the evolution of banking systems in Latin America after the crisis. Section 4 describes the empirical strategy implemented by each country. Section 5 presents the results obtained by the country papers using meta-analysis techniques. We focus first, on how specific banks' indicators (i.e. bank size, liquidity, capitalisation, revenue, funding and profitability) affect the supply of credit, controlling for demand shifters. Then, we analyse how these characteristics affect banks' response to monetary policy shocks. We also evaluate how bank with different characteristics react to changes in global financial conditions and economic policy uncertainty. Section 6 summarises the country specific analyses. Finally, Section 7 concludes.

2. Related literature

Our paper builds on and contributes to the literature on how bank-specific characteristics can strengthen or weaken the effects of monetary policy on credit supply. Within this literature, Kashyap and Stein (2000) was an early and seminal paper to examine how monetary policy can affect the lending decisions of individual banks in the United States. They find that, within the class of small banks, changes in monetary policy affect more those banks with less liquid balance sheets (ratio of securities to assets). Since then a number of studies have explored similar questions, including for other banking systems. For Italian banks, Gambacorta (2005) tests cross-sectional differences in the effectiveness of the bank-lending channel. He shows that the impact of monetary policy on lending is greatest for banks with low liquidity and capitalisation and that are less able to raise uninsured funds. Altunbas et al (2009) find that European banks that make use of securitization activity are more sheltered from the effects of monetary policy changes, but that securitisation provides banks with some flexibility to face changes in market conditions associated with monetary policy movements. Similarly, Altunbas et al (2010) find that bank risk plays an important role in determining the effects of monetary policy on banks' loan supply: low risk banks can better shield their lending from monetary shocks as they have better prospects and easier access to uninsured fund raising. Finally, Gambacorta and Margues-Ibanez (2011) show that changes in banks' business models and market funding patterns modified the monetary transmission mechanism in Europe and the US in the GFC: banks with weaker core capital positions, greater dependence on market funding, and on non-interest sources of income restricted their loan supply more strongly during the period.

A recent branch of literature, closely related to our paper, examines the role of bankspecific characteristics in sheltering banks from external shocks using credit registry data. For Spanish banks, Jimenez et al (2015) study the effects of dynamic provisioning on credit. They find that the build-up of capital buffers during good times helps mitigate the effects of a credit crunch during bad times, making this a preferred policy compared to lowering requirements for lowly capitalized banks in crisis times. For Italian banks, Bolton et al (2016) find that relationship banking is an important mitigating factor in a crisis and that banks with a larger equity cushion are able to perform their relationship-banking role more efficiently. Banerjee et al (2017) analyse the real effects of relationship banking in Italy. They find that following Lehman's default, banks offered lending terms that were more favourable to firms with which they had stronger relationships and that such conditions helped firms maintain higher levels of investment and employment. Cetorelli and Goldberg (2016) study how funding shocks affect the cross-border supply of credit of US banks. Their results show that organizational complexity of bank conglomerates alters the balance sheet composition of banks and their response to funding shocks. Particularly, banks in institutions with more subsidiaries exhibit significantly lower lending sensitivity to changes in own funding conditions. Finally, Neuhann and Saidi (2018) analyse the repeal of the Glass-Steagall act to show that deregulation of universal banks allowed them to finance riskier projects with higher productivity.

Since the common analytical framework of our project follows closely the empirical specification of Jimenez et al (2012), we specifically also review their paper. They use detailed data on loan applications from firms to analyse how reductions in credit availability due to adverse conditions depend on bank balance-sheet strength. They find that the negative effect of monetary policy or low GDP growth on credit availability is stronger for banks with low capital or low liquidity. Their paper shows the advantage of using highly granular data as it enhances the identification of loan supply shifts, and can isolate the effect that bank-specific characteristics have on credit dynamics.

As noted, the confidentiality of credit registry data prevents us to combine the data into a unique dataset. For this reason, we specify a common empirical approach for each country team, and then compile and analyse the results using meta-analysis techniques. Within the project, each country paper followed a similar methodology but different from Jimenez et al (2012), focusing on loan growth instead of on loan applications. This methodology yields comparable cross-country evidence with the added benefit of being able to explore the reasons of heterogeneity within and across countries.

Other efforts have followed the same approach. One example is the initiatives undertaken by the International Banking Research Network (IBRN). Buch and Goldberg (2014) study the magnitude and mechanism for transmission of liquidity shocks through international banks as part of the research conducted by eleven country teams in the IBRN. Their summary of the empirical results show that that no single balance sheet factor affects banks' exposure to liquidity risk in a consistent way across time and across countries or banks. However, balance sheet characteristics of banks matter for differentiating their lending responses, mainly for cross-border lending. In a follow-up project of the IBRN, Buch and Goldberg (2017) summarise the results from fifteen central bank studies on how international spillovers of prudential policy can change and their effects on bank lending growth. They find that bank-specific factors such as balance sheet conditions and business models drive the amplitude and direction of spillovers to lending growth rates. Another project that compile results from individual countries studies based on a common approach are the research projects developed by the BIS to study the impact of macroprudential policies on credit growth and their interaction with monetary policy. Gambacorta and Murcia (2017) present the results by eight countries and find that, on average, macroprudential policies have been effective in dampening credit cycles and that these policies are more effective if used as a complement to monetary policy. They also find that bank-specific characteristics can influence the impact of macroprudential policies on credit policies had a greater effect on less stable financial institutions in Colombia and less strongly capitalized and liquid banks in Brazil. This builds on these literatures, to show using credit registry data, bank-specific characteristics can strengthen or weaken the effects of monetary policy on credit supply.

3. Evolution of banking systems in Latin America after the great financial crisis

This section characterises the main trends and changes in banks' structure and characteristics in Latin America during the post-crisis period. The banking sector globally is undergoing a profound structural change because of the combined impact of the post-crisis economic environment, changes in regulation, and new financial innovation (see CGFS, 2018). The systems in Latin America are experiencing these pressures as well, but due to a number of specific factors, there are some notable differences from global trends.

In terms of monetary policy, after the GFC, major advanced economies lowered their monetary policy rates to near zero levels and long-term interest rates fell as well to historically low level. The response in Latin America was slightly different due to varying starting cyclical conditions and structural vulnerabilities. Central banks in Latin America did not immediately start a period of easing in monetary conditions, but as the effects of the global credit crunch started to affected domestic activity as well, monetary authorities progressively lowered interest rates to historically low levels (Graph 1). Once the effects of the GFC started to dissipate, and faced with renewed inflationary pressures, most Central Banks started to raise their policy rates. The pace of monetary normalisation has been heterogeneous, however, and policy rates have not returned to levels observed before the GFC. Output growth in the region recovered after a drop in 2015, but forecasted growth is lower than pre-crisis levels and well below the forecast for other emerging economies.

Despite lower output growth in the post-crisis period, private sector credit has continued to expand in Latin America. Financial deepening, measured as total credit to the private financial sector as a percentage of GDP, shows a rising trend (Graph 2, left panel). The size of banking systems in Latin America during the last ten years also shows a steady growth, with banks' total assets to GDP increasing by 63 per cent on average (Graph 2, centre panel). The number of banks in the region has increased in Colombia and Peru, but

decreased in Brazil, Chile, and Mexico, in part due to mergers and acquisitions. Changes in concentration ratios have been consequently heterogeneous in the region.⁵

Before the GFC, banks generally showed low non-performing loans (NPLs). After the GFC, growth in NPLs edged up in all advanced economies, reflecting rising risks in the global banking system. However, by 2017 most advanced economies saw a decline in the share of NPLs to total loans below 1.5 percent, with the only exception being the Euro Area. The behaviour of NPLs differed by country in the Latin America region (Graph 2, right panel). From 2007 to 20013, the share of NPLs decreased in Brazil and Colombia, while it increased in Chile, Mexico and Peru. In the last four years, the share of NPLs has been lower in Chile and Mexico, while rising in Brazil, Colombia, and Peru.

In terms of regulation and supervision, post-crisis, there was a renewed effort to introduce a global regulatory framework to strengthen bank resilience. The main objective was to increase requirements for higher-quality capital and liquidity to reduce system-wide risks to financial stability. Banks in Latin America already had high levels of regulatory capital compared to the rest of the world before the crisis (Graph 3, left panel). The high pre-crisis levels of regulatory capital mitigated the turmoil of the GFC and reflected lessons learned from previous crises. Banks have accompanied the post-crisis expansion of their balance sheets and the increase in the density of risk-weighted assets with higher equity capital, maintaining capital ratios stable (Graph 3, centre panel). For most countries in Latin America, the median capital ratios are still above the median ratio of banks in other advanced economies.

Another post-crisis change has been a shift in the funding composition of banks. Banks in advanced economies have reduced their reliance on wholesale funding while increasing the share of stable sources of funding, such as customer deposits. For banks in Latin America, customer deposits have traditionally been the main source of funding. However, greater access to international capital markets has allowed banks to diversify their sources of funding. Particularly there has been an increase in the share of long-term funding (Graph 3, right panel). Finally, a common trend in the region has been a reduction in the use of interbank borrowing and an increase in the use of wholesale funding.

Before the crisis, international banking activity grew faster than world economic activity and banking became increasingly global (McCauley et al, 2017). There was also a sharp increase in bank claims on Latin American banks, which suddenly reversed upon the onset of the crisis (Graph 4, left panel). However, as international banks recovered, there was an increase in bank claims on Latin American banks, particularly from banks in the United States. This trend started to flatten around 2012 and has started to decrease in recent years. However, some of this decline has been offset by an inflow of securities as banks and other corporations assessed international bond markets.

At the same time, there has been a higher presence of Latin American banks within their own region, especially from Colombian banks to Central America (Morales et al, 2018). This trend is in place also for emerging markets in other jurisdictions. Demirgüç-Kunt et al.

⁵ The number of banks has increased from 2007 to 2017 by 13 in Colombia and 5 in Peru; and decreased by 29 in Brazil, 7 in Chile and 1 in Mexico. From 2007 to 2017 concentration ratios, measured as the share of the five largest banks in total banking system assets, have increased for Brazil, Chile and Colombia, while they have decreased for Mexico and Peru.

(2018) document that in the last years, developing country international banks do more business in other developing countries, in what they define as a "South-South" trend. They also stress that the most important factor for banks' expansion is the stability of their funding sources.

Measured bank profitability around the world was at an all-time high before the crisis, supported by what turned out to be unstainable leverage and risk-taking. During the crisis, banks in the United States and Europe were heavily hit and recorded relevant losses. Banks in Latin America were better able to weather the crisis, but return on equity (ROE) still decreased (Graph 4, centre panel). There is no common trend of profitability in the region. In Brazil and Mexico, there was a sharp decline of ROE during the crisis. After the crisis, profitability started to recover, albeit at a slow pace. On the other hand, in Chile, Colombia, and Peru the level of ROE has continuously decreased for the past decade.

Reflecting the impact of the GFC and others factors banks have been adjusting their business models. Revenue shares can capture these shifts in business models as these reflect the type of activities a bank takes part in. Consistent with global trends, for all countries in Latin America, there has been a clear change in the revenue mix in the last decade (Graph 4, left panel). Banks in the region, except in Brazil, have increased their share of net interest revenues while reducing the share of net securities revenues. This shift can point to a change towards more traditional lending activities in these countries. In Brazil, we observe an opposite trend, reflecting a diversification in bank activities.

To further analyse the evolution of how bank-specific characteristics (BSC), we classify banks in Latin America into three categories: trading, universal and commercial banks.⁶ We base the classifications on thresholds of balance sheet data. In broad terms, trading banks have a high share of trading asset securities on their balance sheet, whereas commercial banks have a low share of trading account securities and a substantial share of loans on their balance sheets. Universal banks cover the middle ground.⁷ Furthermore, we only consider banks that were present in the database throughout 2007 to 2017.

We then consider the change across business models during the period after the GFC. We can document how banks transitioned from one model to another (Graph 5). Banks transitioned from the trading and universal business model to the commercial business model. Changes in funding and revenue strategies can explain this move. Banks stopped tapping into riskier sources of funding and concentrated on traditional banking activities. In the past five years, the banking systems of Latin America have become more sophisticated and banks have started once again to increase their market making activities. The dominant business model is still the universal business model. The trading business

⁶ We follow a methodology similar to the one applied in the Basel Committee on Banking Supervision (Saunt and Fub (2012)). Another approach is to use statistical analysis to determine business models. Based on balance sheet indicators a number of studies use cluster techniques to identify groups of banks that are similar. For example, Roengpitya et al (2017) distinguish between retail-funded banks, wholesale funded banks, universal banks, and trading banks. Data availability precluded us from applying this approach.

⁷ Banks with a ratio of trading account securities to total assets of more than 30% were classified as trading banks with less than 30% and more than 2% were classified as universal banks; and banks with less than 2% as commercial banks. There were some additional adjustments made for the classification. Banks classified as either commercial or universal with a loan to assets ratio of less than 15% were excluded from the analysis. For some banks, there was no information on trading account securities. In this case, if the securities to asset ratio was greater than 15% per cent the bank was classified as universal, otherwise it was classified as commercial

model continues to decrease in both number of banks and share of assets. Even though the number of commercial banks increased, their share of assets in the banking system is lower today.

4. Empirical strategy

This describes the methodology implemented by each country team to analyse how bankspecific characteristics (BSC) and banks' business models affect the supply of credit. To do so, we classify BSC into one of seven categories:

- 1. **Main indicators:** size (log of total assets), bank capital ratio (equity-to-total assets), and bank liquidity ratio (cash and securities over total assets).
- 2. **Risk indicators:** incidence of loan-loss provisions, share of non-performing loans, share of doubtful loans, securitisation activity, and share of write-offs.
- 3. **Revenue mix (commercial business model):** share of net fees and commission income (net fees and commissions to operating income), retail loans as a share of total loans, and broad credit.
- 4. **Revenue mix (universal business model):** diversification ratio (non-interest income to total income), share of trading income (trading income to operating income), and assets held for trading as a share of total assets.
- 5. **Stable sources of funding:** share of deposits over total liabilities, share of short-term funding, share of long-term funding.
- 6. **Volatile sources of funding:** wholesale funding ratio, funding in foreign currency, and funding from foreign sources.
- 7. **Profitability:** return on assets, return on equity, efficiency ratio (operating costs to total income), number of employees per total assets, number of branches per total assets.

Each country used different BSC depending on data availability. The first part of Table 1 provides a summary on the indicators used by each country team. The second part shows the expected signs of the direct impact on bank lending growth of bank-specific characteristics and their interaction with the monetary policy/global shock indicator.

To explore the effects of the evolution of banks' business models, we use detailed credit register data for each country in the region. The use of these data allows the proper identification of credit supply, controlling for demand shifts. Credit register data are highly confidential, which means that it is not possible to merge the data from individual countries in a unique dataset. However, to allow for an international comparison, the econometric analysis at the country level used the same modelling strategy and data definition (as far as data sources allow in terms of coverage, collection methods and definitions).⁸ We enhance the identification of the model by only considering firms that have loans with multiple banks. This determines a drop of the representativeness of the sample, but allows

⁸ This approach has been followed by Buch and Goldberg (2017) and Gambacorta and Murcia (2017).

us to insert in the specifications both bank and firm*time fixed effects. The firm*time fixed effects absorb time variant firm specific demand shocks (see Khwaja and Mian (2008)).

We consider both domestic monetary policy and global shock. The monetary policy shocks are defined as the changes in the policy interest rate. We consider four additional sources of shocks (Graph 6).

- 1. **Global financial uncertainty:** measured by the VIX index (dummy for high volatility period).
- 2. **Global liquidity:** measured by the Wu-Xia (2016) shadow rate for the US monetary policy.
- 3. **Economic policy uncertainty (EPU):** measured by the Baker, Bloom and Davis (2016) index (dummy for high-level periods).
- 4. **Global commodity prices:** measured by a commodity price index (dummy for low price periods).

4.1 Role of bank-specific characteristics on the supply of credit

The first part of the empirical analysis focuses on how bank specific characteristics impact lending. We use the following panel equation:⁹

$$\Delta \log \operatorname{Loan}_{f,b,t} = \beta X_{b,t-1} + \alpha_b + \gamma_{f,t} + \varepsilon_{f,b,t}$$
(1)

The dependent variable $\Delta \log \text{Loan}_{fbt}$ is the change in the logarithm of outstanding loans by bank *b* to firm *f* at time *t*. X_{bt-1} is the vector of BSCs; α_b correspond to time invariant bank fixed effects; and $\gamma_{f,t}$ to time variant firm fixed effects. It is important to note that by the inclusion of bank fixed effects we can interpret the coefficient estimates as variation within banks over time. The main question to answer is how bank-specific characteristics affect the loan supply.

Each country team ran the regression including first the different categories of BSC, one at the time. To reduce collinearity problems, the last specification includes those bank-characteristics from each block that had a statistically significant coefficient in the individual regressions.¹⁰

4.2 Bank lending channel

We then test how the supply of credit of banks with different characteristics react to domestic monetary shocks. To this end, we extended the model in the following way:

$$\Delta \log \operatorname{Loan}_{fbt} = \beta X_{bt-1} + \sum_{j=0}^{3} \delta_j (\Delta i_{t-j} * X_{bt-1}) + \alpha_b + \gamma_{f,t} + \varepsilon_{fbt}$$
(2)

In this specification, Δi_t is the quarterly change in the monetary policy rate. For simplicity, we included the contemporaneous effect of the monetary policy stance plus three lags (looking at the total effect after one year); however, each country team could use the number of lags that they found was more suitable. Following the bank lending channel

⁹ The model is based on Jimenez et al (2012) and Gambacorta and Marques-Ibanez, (2011).

¹⁰ Given their importance in the bank lending channel literature, size, liquidity and capital were always included in the last regression, even if they were not statistically significant in the main indicators block (Gambacorta (2005)).

literature, we identify supply shifts to monetary policy shocks by means of the statistical significance of the coefficients in the vector δ_i .

4.3 Impact of global factors

The last part of the analysis evaluates whether the impact of global factors/external conditions could change the way BSCs affect the supply of credit. We write the model the following way:

$$\Delta \log \operatorname{Loan}_{fbt} = \beta X_{bt-1} + \lambda (C_t * X_{bt-1}) + \alpha_b + \gamma_{f,t} + \varepsilon_{fbt}$$
(3)

where C_t corresponds to a global variable that characterises external conditions.

This part of the analysis focused on how certain bank-specific characteristics can build resilience against global shocks. Each country team had the option to express the shock in level or to calculate a dummy variable that took the value of one during extreme periods. Depending on sample availability of the database, country teams adjusted the percentile to calculate the dummy.

5. Summary of results using meta-analysis techniques

We combine the results obtained from each country using meta-analysis techniques exploiting the fact that all studies have the same design. The essence of meta-analysis is to obtain a single estimate of the effect size by computing a weighted average of the studies' individual estimates of the effect. We focus on the coefficients reported by each country for the three equations in our empirical strategy. The set of coefficients of interest from equation 1 are the ones associated with the BSC.¹¹ For equation 2, we focus on the coefficients of the interaction terms between BSC and the monetary policy shock. Finally, the relevant coefficients in equation 3 are related to the interaction terms between BSC and the global shocks.

We conduct our meta-analysis under the assumption of a random effects model. We chose this model since there are important sources of heterogeneity in the individual country studies that arise from the institutional and regulatory frameworks of credit provision as well as the peculiarities of each country's banking system. Random effects models consider both the variance around the mean of the estimated effect and the between-study variance, which is incorporated into the calculation of the weights of each study in the estimated mean effect (see Appendix B). We report our results in two ways. First, we present a summary table for each equation and shock with the statistics on heterogeneity among studies and the estimated mean aggregate effect. Then, we display the most interesting and significant individual and aggregate estimates in forest plots.¹²

¹¹ The number of coefficients used for the meta-analysis of certain categories of BSC can be greater than the number of reporting countries. This happens when a country reported coefficients related to different BSC but that fall into the same category. For example, Mexico reported the coefficients related to non-performing loans and write-offs, both of which would fall into the risk indicators category.

¹² This graph shows horizontal lines for each study, depicting estimates and confidence intervals. The size of the plotting symbol for the point estimate in each study is proportional to the weight that each study contributes to the metaanalysis. A diamond marks the overall estimate and confidence interval.

5.1 Impact of bank-specific characteristics on lending growth

Table 2 shows the results of the effects of BSC on the supply of credit. The mean effect estimate shows a positive and significant relationship between the growth of credit and assets, capital, and revenue indicators of commercial business models. On the other hand, the BSC that have a negative mean effect on the supply of credit are risk indicators, revenue indicators of universal business models, and volatile sources of funding. From the statistics, we observe a high level of heterogeneity in effect sizes.

We present a graphical summary of the results using forest plots. In a forest plot, the rows correspond to the coefficient obtained for each country and the size of the grey squares represents the weights in the estimated mean effect. The x-axis represents the level of the coefficient and black dots represent the country's coefficients. A line that represents the confidence interval of the estimated value crosses each point. The blue diamond represents the estimated range of the sum of interactions using random effects analysis. All country studies found that well-capitalised banks grant more credit (Graph 7). The estimated coefficients imply that a 1-percentage point increase in the bank capital ratio increases the growth in bank credit across studies between 0.14 to 0.57 percentage points, with an estimated mean effect of 0.26 percentage points. This result is qualitatively similar to that obtained by Gambacorta and Shin (2018): a 1-percentage point increase in the equity-tototal-assets ratio is associated with a 0.6 percentage point increase in total lending growth. These results indicate that a larger capital base reduces the financing constraint faced by the banks allowing them to supply more loans to the economy. All studies found that banks with a high level of risk grant (ex-post) less credit (Graph 8). In this case, there was an array of measures used by each country but the estimated mean implies that a 1-percentage point increase in risk indicators reduced the growth of credit by 0.48 percentage points.

Country studies found that a universal business model, other things being equal, is typically associated with a lower supply of credit (Graph 9). Particularly, banks with higher diversification ratios in Colombia, Mexico and Peru, banks with high trading income in Peru, and banks with a high ratio of assets held for trading in Mexico tend to grant less credit. On the other hand, banks with a commercial business models grant more credit (Graph 10). In this case, banks with a higher share of net fees and commissions in Brazil and Peru, banks with higher broad credit in Brazil, and banks with a higher share of retail loans in Chile grant more credit. Finally, all countries found that indicators of volatile sources of funding have a negative impact on credit growth. Particularly, banks with a high share of wholesale funding in Brazil and Peru, and banks with a high share of funding in foreign currency in Brazil, Chile and Mexico grant less credit.

5.2 Impact of bank-specific characteristics on monetary shocks

Table 3 shows the mean effect estimates of the interaction between BSC and changes in the monetary policy indicator. We observe a higher level of heterogeneity in the significance of the results among country studies. In general, we find that within banks, those with higher capital are less affected by monetary policy shocks, while those with commercial business models are more affected by monetary policy shocks. The first result is well established in the bank lending channel literature, while the latter is probably due to the higher dependence of commercial banks on deposits that are directly affected by changes in the monetary policy rate. All countries, except for Peru, found that wellcapitalised banks are more sheltered against monetary policy shocks (Graph 11). On the other hand, banks in Chile with a high share of retail loans and banks in Colombia with a high share of net fees and commissions reduce more their credit supply when faced with a monetary policy shock (Graph 12).

5.3 How banks with different characteristics react to global shocks

Table 4 shows the estimated mean effect of the interaction between BSC and the highglobal risk dummy. We find that, in general, within banks, those that are well-capitalised, with high liquidity and more stable sources of funding are sheltered against risk shocks. From the individual studies, Brazil found that more diversified banks reduce less their credit supply when faced with risk shocks. Banks in Mexico with a high share of funding from foreign sources are more vulnerable against risk shocks.

After the GFC, there was a period with excess liquidity in the market and characterised by accommodative monetary policies in advanced economies. We analyse the response of credit to the high liquidity period by the interaction between BSC and the Federal fund shadow rate (Table 5). The estimated mean effect shows that within banks, those that are large, with high profitability and commercial business models reduce more their credit supply when faced with a liquidity shock. On the other hand, banks in Brazil and Colombia that are well capitalised and banks in Mexico that are liquid and have low risk indicators increase their credit supply during periods of high liquidity.

Turning to the interaction between BSC and periods of high economic policy uncertainty, we find that in general, within banks, those that are well capitalised with stable sources of funding are more sheltered against these shocks (Table 6). From the individual studies, the BSC that weaken the ability of banks to supply credit against economic policy uncertainty shocks are a high share of net fees and commissions in Colombia, and a high diversification ratio and share of funding from foreign sources in Mexico.

Finally, we present the results of the interaction between BSC and the dummy for periods of low commodity prices. The estimated mean effect shows that, in general, banks that are large and well capitalised reduce less their credit supply when faced with commodity price shocks. Country studies found that the BSC that shield the credit supply against these shocks are a higher share of trading income in Brazil and a higher share of long term funding in Mexico.

6. Summary of country papers

The above results have been corroborated by country studies that take into account specific institutional details in each jurisdictions. We summarise below the main results of the five country papers, noting where the studies qualify some of the results reported in the section above.

Brazil. Gonzalez (2018) estimates a bank balance-sheet lending channel for Brazil and its real-effects for firms. Similarly to Kashyap and Stein (2002), he finds that the channel operates through smaller banks and those with lower capital and liquidity ratios. However, capital is the strongest channel among those. These results are robust to interactions with all relevant bank characteristics, and "horseracing" against several macroeconomic variables typically connected to the business cycle and embedded in the Taylor rule such as GDP, inflation and expected inflation, as well VIX, changes in commodity prices, US fed funds rate and short shadow rate. Firm-level results corroborate with such findings and reveal the real effects of the lending channel in Brazil. Firms connected to lower capitalized banks face a deeper credit, employment, and investment decline after a tightening of the overnight federal funds rate.

Chile. Birón, Córdova and Lemus (2018) find that well-capitalised banks reduce less their credit supply when faced with a monetary policy tightening. Their analysis of the effect of global shocks finds that banks that transmit commodity price changes to lending more aggressively have a higher share of retail loan, lower share of deposit, and poor asset quality. All the above results are robust to the exclusion of a government-owned bank. However, when removing this bank from the sample all the interactions between private banks' characteristics and change in monetary policy increase.

Colombia. Morales, Osorio and Lemus (2018) evaluate the extent to which the strength of the bank-lending channel has changed because of the expansion of Colombian banks abroad, widely considered the most important structural change of the Colombian banking system in recent years. The internationalization of domestic banks is found to reduce the power of the bank-lending transmission channel of domestic monetary policy, consistent with a cushioning role provided by the operation of domestic banks overseas. The effect of the share of foreign funding seems to weaken when the internationalization of Colombian banks is more intense.

Mexico. The results by Cantú, Lobato, López and López-Gallo (2018) highlight the importance of strong balance sheets for the provision of credit in Mexico. They find that bank-specific characteristics that affect positively the supply of credit in Mexico are size, high capital, lower share of riskier loans, a commercial business model, and high long-term funding. Second, they find that those banks that reduce less their credit supply when there is a tightening of monetary policy are liquid, well-capitalised, have lower credit risk, are more efficient, more reliant on short-term funding and a have a relatively low share of funding from foreign sources. Finally, the Mexican case study finds that banks' characteristics that build resilience against external shocks are high liquidity, high capital, less income diversification, high share of short-term and long-term funding, and low share of funding from foreign sources.

Peru. Bustamante, Cuba and Tambini (2018) find that that well-capitalized, high-liquidity, low-risk, more profitable banks tend to grant more credit in Peru. They also study the bank-lending channel in Peru and find that banks that are large (in terms of assets) and more liquid reduce less their credit supply when faced with monetary policy shocks. On the other hand, banks with a higher share of non-interest income to total income and higher share of net fees and commission income to operating income are more affected by changes in monetary policy rate. Finally, bank capitalisation and risk play an important role in shielding banks against external shocks.

7. Conclusions

[to be added]

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Appendix A: Graphs and Tables

Economic outlook in Latin America

Graph 1



¹ For Brazil, target for SELIC overnight rate; for Chile, monetary policy rate; for Colombia, expansion minimum intervention rate; for Mexico, overnight policy rate (prior to 2008, bank funding rate); for Peru, reference rate. ² Year-on-year changes in consumer price index. ³ Forecast shown as dots. ⁴ Weighted average based on GDP and PPP exchange rates for Chinese Taipei, The Czech Republic, Hong Kong SAR, Hungary, India, Indonesia, Korea, Malaysia, Singapore, the Philippines, Poland, Russia, Thailand and Turkey. Source: Bloomberg; Datastream; OECD; national sources;

Banking systems in Latin America

Graph 2



Credit to the non-financial private Total assets sector

Non-performing loans ratio



² For Brazil data in 2016 corresponds to data in 2015. For Peru data in 2007 corresponds to data in 2009. ³ Decomposes ¹ Median ratios. the change in the Common Equity Tier 1 (CET1) capital ratio into additive components. The total change in the ratios is indicated by dots. The contribution of a particular component is denoted by the height of the corresponding segment. A negative contribution indicates that the component had a capital ratio-reducing effect.

Source: Fitch Connect.



¹ Outstanding cross-border bank claims of reporting banks on Brazil, Chile, Colombia, Mexico and Peru. Claims include bank loans and other instruments except banks' holding of debt securities. ² Austria, Belgium, Denmark, France, Finland, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. ³ China, Chinese Taipei, India, Japan, Korea, and the Philippines. ⁴ All reporting institutions minus shown reporting countries. ⁵ Sum of net gain on assets at FV through income statement, net insurance income and other operating income.

Sources: Fitch Connect; BIS locational banking statistics.

Graph 4

Transition across models in Latin America



¹ Percentages do not add up to 100% since there are banks without classification. Source: Fitch Connect.

Global shocks

Graph 6





Graph 7: Forest plot of the effects of bank capital on credit

Graph 8: Forest plot of the effects of bank risk on credit





Graph 9: Effects of revenue indicators in universal business models on credit

Graph 10: Effects of revenue indicators in commercial business models on credit





Graph 11: Effects of volatile sources of funding on credit

Graph 12: Interaction effect between capital and monetary policy shock





Graph 13: Interaction effect between revenue mix (commercial business models) and monetary policy shock

Bank specific characteristics us	ed in the	analysis by each country					Table 1
Variable Name	Expected Sign	Basic Argument	BR	CL	СО	MX	PE
Main Indicators							
In (total assets)	+/ -	Large banks might isolate better adverse shocks (+). In case of interal capital markets or strong lending relationship between small firms and small banks (-).	х	х	х	х	х
Bank capital ratio	+	Well-capitalised banks more likely to expand supply of loans.	Х	Х	Х	Х	Х
Bank liquidity ratio	+	Highly-liquid banks more likely to expand supply of loans.	Х	Х	Х	Х	Х
Risk indicators							
Loan-loss provisions as a share of total loans	+/ -	Depending on the regulation reagrding levels of loan-loss provision, it can either signal high risk (-) or the strength of banks against losses (+).		х	х		х
Non-performing loans as a share of total loans	+/ -	Riskier banks might expand lending by more, especially versus risky segments (+). Alternatively if forced by regulation to contain their credit portfolio (-).	х			х	х
Doubtful loans as a share of total loans	-	As the share of doubtful loans and write-offs increases, repayment of loans starts to be an issue. Banks will			х		х
Write-offs as a share of total loans	-	be less able to raise additional funds, which would affect negatively the credit supply.				х	
Securitization activity	+	Securitisation as capital relief and funding source.					Х
Revenue mix (Commercial Business Model)							
Share of net fees and comission income	+		Х	Х	Х		Х
Retail loans as a share of total loans	+	to be added		Х			
Broad credit	+		Х				
Revenue mix (Universal Business Model)							
Diversification ratio	+/ -	More profitable non-interest income can lead to more lending, but if it is volatile it can lead to less lending.	Х		Х	Х	Х
Share of trading income	-	to be added	Х	Х		Х	Х
Assets held for trading as a share of total assets	-				Х	Х	Х
Stable sources of funding							
Shares of deposits over total liabilities	+	Banks with more deposti funding (stable) could expand more the supply of loans.					Х
Share of short-term funding	+/-	Banks with more short-term funding are more subect to market conditions.		Х	Х	Х	Х
Share of long-term funding	+	Long-term sources of funding imply less risk, allowing banks to grant more loans.				Х	
Volatile sources of funding							
Wholesale funding ratio	-	Banks with more wholesale funding are more subject to market conditions.	Х				
Share of funding in foreign currency	-	High dependance on foreign sources of funding and high share of funding in foreign currency increases the	Х	Х	Х		X
Share of funding from foreign sources	-	vulnerability of banks against the exchange rate and volatile capital flows, which would reduce lending.				Х	Х
Profitability							
Efficiency ratio	+		Х			Х	X
Number of employees per total assets	+	Mare profitable and efficient banks are more likely to surround their conditions by					X
Number of branches per total assets	+	more promable and emclent banks are more likely to expand their credit supply.	V	V			X
ROE (12 months)	+		X	X	V		X
Number of debtors	+		145.976	104 100	2 210 000	112.005	4 192
Number of deptors			145,870	104,109	3,210,000	112,905	4,182
Time period			90 200401-201604	200001-201604	200701-201702	42	200401-201504
			4 766 376 00	4 620 002 00	3 185 036 00	2 661 018 00	111 072 00
003017000113			4,700,570.00	4,023,302.00	3,103,030.00	2,001,010.00	111,072.00

•									
	Assets	Capital	Liquidity	Risk Indicators	Revenue Universal BM	Revenue Commercial BM	Stable sources of funding	Volatile sources of funding	Profitability
Q* (1)	3.52	10.52**	15.50***	17.96***	4.37	3.24	11.83***	36.66***	1.91
Degrees of freedom	4	4	4	6	4	3	1	5	2
I ² (2) (%)	0.00	61.99	74.19	66.60	8.41	7.36	91.54	86.36	0.00
τ ² (3)	0	0.0161	0.0014	0.0522	0.0001	0.0006	0.0360	0.0015	0
Random effects mean (4)	0.010**	0.26***	0.00	-0.48***	-0.09***	0.15***	0.18	-0.05**	0.00
95% confi. interval	0.0004 to 0.0188	0.1130 to 0.4132	-0.0477 to 0.0522	-0.7201 to - 0.2369	-0.1220 to 0.0579	0.0658 to 0.2369	-0.0988 to 0.4492	-0.0968 to -0.0097	0.0011 to 0.0012

Table 2

Table 3

Equation 1: Effects of Bank Characteristics on Credit

Equation 2: Interaction between BSC and Monetary Policy Shock

Risk Profitability Assets Capital Liquidity Revenue Revenue Stable Volatile Indicators Universal Commercial sources of sources of ΒM funding BM funding Q* (1) 10.6** 14.2*** 37.8*** 59.26*** 26.13*** 2.15 6.10** 45.58*** 7.53* Degrees of 4 2 4 4 4 2 3 6 3 freedom I² (2) (%) 67.21 62.31 71.87 89.88 84.69 6.87 93.42 60.17 89.42 τ^{2} (3) 0.0000 0.0240 0.0103 0.5352 0.0608 0.0005 0.0033 0.0840 0.0086 Random -0.0023 0.1601* -0.0796** 0.105 0.0017 effects 0.0619 -0.4799 0.0286 -0.1817 mean (4) -0.0104 -0.0108 -0.0411 -1.1274 -0.2186 -0.1572 0.0224 -0.4805 -0.1193 95% confi. to to to to to to to to to interval 0.0058 0.3309 0.1648 0.1675 0.2759 0.0021 0.1875 0.1172 0.1226

Notes: (1) The Q Measure evaluates the level of homogeneity/heterogeneity among studies. It is calculated as the weighted squared difference of the estimated effects with respect to the mean. The statistical distribution of this measure follows a χ^2 distribution. The null hypothesis of the test assumes homogeneity in the effect sizes. (2) This percentage represents the magnitude of the level of heterogeneity in effect sizes and it is defined as the percentage of the residual variation that it is attributable to between study heterogeneity. It is defined as the difference between the Q measure and the degrees of freedom divided by the Q measure. Although there can be no absolute rule for when heterogeneity becomes important, Harbor and Higgins (2008) tentatively suggest adjectives of low for I2 values between 25% and 50%, moderate for 50%-75% and high for values larger than 75%. (3) τ^2 is a measure of population variability in effect sizes. It depends positively on the observed heterogeneity (Q measure) and its difference with respect to the degrees of freedom. Given the expected value of Q measure under the null hypothesis of homogeneity is equal to the degrees of freedom; a homogeneous set of studies will result in this statistic equal to cero. Under the presence of heterogeneity this estimate should be different from cero. (4) It corresponds to the weighted average of coefficients reported in different estimations. The weights are calculated considering the sampling fluctuation of each effect size (standard error per reported coefficient) and estimated population variance of effect sizes (τ^2). ***,*** and * denote significance at the 1%,5% and 10%, respectively.

Equation 3: Interaction between BSC and high risk dummy											
	Assets	Capital	Liquidity	Risk Indicators	Revenue Universal BM	Revenue Commercial BM	Stable sources of funding	Volatile sources of funding	Profitability		
Q* (1)	2.19	2.30	1.45	8.05	20.10***	3.70	3.00	21.52***	0.24		
Degrees of freedom	4	4	4	5	5	2	3	4	1		
I ² (2) (%)	0.00	0.00	0.00	37.90	75.12	45.90	0.00	81.41	0.00		
τ ² (3)	0.0000	0.0000	0.0000	0.1005	0.0189	0.0279	0.0000	0.0314	0.0000		
Random effects mean (4)	-0.0013	0.21***	0.0514***	-0.1303	-0.0431	0.1279	0.0597***	-0.1348	0.0377		
95% confi. interval	-0.0056 to 0.0029	0.1165 to 0.3106	0.0282 to 0.0747	-0.5895 to 0.3290	-0.1812 to 0.0949	-0.1375 to 0.3934	0.0295 to 0.0900	-0.3169 to 0.0472	-0.0803 to 0.1557		

Equation 3: Interaction between BSC and FFR (shadow rate)

Table 5

	Assets	Capital	Liquidity	Risk Indicators	Revenue Universal BM	Revenue Commercial BM	Stable sources of funding	Volatile sources of funding	Profitability
Q* (1)	2.81	11.37	28.19	49.62	11.92	4.00	7.96	48.56	0.69
Degrees of freedom	4	4	4	4	3	3	1	4	3
I ² (2) (%)	0.00	64.81	85.81	91.94	74.84	25.05	87.44	91.76	0.00
τ ² (3)	0.0000	0.0020	0.0008	0.1580	0.0017	0.0002	0.0030	0.0026	0.0000
Random effects mean (4)	-0.002***	0.0364	0.0115	-0.2823	0.0229	-0.0292**	0.0431	-0.026	-0.0199**
95% confi. interval	-0.0032 to - 0.0005	-0.0155 to 0.0883	-0.0185 to 0.0415	–0.6634 to 0.0988	-0.0242 to 0.0699	-0.0556 to - 0.0028	-0.0384 to 0.1246	-0.0738 to 0.0218	-0.0371 to - 0.0028

Notes: (1) The Q Measure evaluates the level of homogeneity/heterogeneity among studies. It is calculated as the weighted squared difference of the estimated effects with respect to the mean. The statistical distribution of this measure follows a χ^2 distribution. The null hypothesis of the test assumes homogeneity in the effect sizes. (2) This percentage represents the magnitude of the level of heterogeneity in effect sizes and it is defined as the percentage of the residual variation that it is attributable to between study heterogeneity. It is defined as the difference between the Q measure and the degrees of freedom divided by the Q measure. Although there can be no absolute rule for when heterogeneity becomes important, Harbor and Higgins (2008) tentatively suggest adjectives of low for I2 values between 25% and 50%, moderate for 50%-75% and high for values larger than 75%. (3) τ^2 is a measure of population variability in effect sizes. It depends positively on the observed heterogeneity (Q measure) and its difference with respect to the degrees of freedom. Given the expected value of Q measure under the null hypothesis of homogeneity is equal to the degrees of freedom; a homogeneous set of studies will result in this statistic equal to cero. Under the presence of heterogeneity this estimate should be different from cero. (4) It corresponds to the weighted average of coefficients reported in different estimations. The weights are calculated considering the sampling fluctuation of each effect size (standard error per reported coefficient) and estimated population variance of effect sizes (\tau2). ***, ** and * denote significance at the 1%, 5% and 10%, respectively.

	Assets	Capital	Liquidity	Risk Indicators	Revenue Universal BM	Revenue Commercial BM	Stable sources of funding	Volatile sources of funding	Profitability
Q* (1)	4.17	0.80	6.49	3.22	16.87***	5.55	2.13	16.82***	0.25
Degrees of freedom	4	4	4	2	3	3	2	3	1
I ² (2) (%)	4.15	0.00	38.39	37.97	82.22	45.94	6.16	82.16	0.00
τ ² (3)	0.00	0.00	0.00	0.59	0.03	0.01	0.00	0.02	0.00
Random effects mean (4)	0.0028	0.24***	-0.011	-0.8757	0.0388	0.0225	0.0927***	-0.092	0.0354
95% confi. interval	-0.0062 to 0.0007	0.1515 to 0.3290	-0.0694 to 0.0474	-2.2024 to 0.4510	-0.1606 to 0.2381	-0.0829 to 0.1279	0.0299 to 0.1554	-0.2616 to 0.0776	-0.1030 to 0.1737

Equation 3: Interaction between BSC and high economic uncertainty dummy

Equation 3: Interaction between BSC and low commodity prices dummy

Table 7

Table 6

	Assets	Capital	Liquidity	Risk Indicators	Revenue Universal BM	Revenue Commercia I BM	Stable sources of funding	Volatile sources of funding	Profitability
Q* (1)	1.02	2.86	50.54***	21.36***	16.69***	0.02	52.39***	52.14***	11.76**
Degrees of freedom	4	4	4	4	4	1	3	3	4
I ² (2) (%)	0.00	0.00	92.09	81.27	76.03	0.00	94.27	94.25	66.00
τ ² (3)	0.00	0.00	0.00	1.32	0.01	0.00	0.00	0.07	0.01
Random- effects mean (4)	0.0003***	0.01***	0.0068	-0.6688	0.0077	0.0726	0.0627	-0.1670	0.0186
95% confi. interval	-0.0005 to -0.0001	0.0060 to 0.0210	–0.0564 to 0.0699	-1.8471 to 0.5095	-0.0869 to 0.1023	–0.0485 to 0.1937	-0.0157 to 0.1411	-0.4405 to 0.1064	-0.0947 to 0.1320

Notes: (1) The Q Measure evaluates the level of homogeneity/heterogeneity among studies. It is calculated as the weighted squared difference of the estimated effects with respect to the mean. The statistical distribution of this measure follows a χ^2 distribution. The null hypothesis of the test assumes homogeneity in the effect sizes. (2) This percentage represents the magnitude of the level of heterogeneity in effect sizes and it is defined as the percentage of the residual variation that it is attributable to between study heterogeneity. It is defined as the difference between the Q measure and the degrees of freedom divided by the Q measure. Although there can be no absolute rule for when heterogeneity becomes important, Harbor and Higgins (2008) tentatively suggest adjectives of low for I2 values between 25% and 50%, moderate for 50%-75% and high for values larger than 75%. (3) τ^2 is a measure of population variability in effect sizes. It depends positively on the observed heterogeneity (Q measure) and its difference with respect to the degrees of freedom. Given the expected value of Q measure under the null hypothesis of homogeneity is equal to the degrees of freedom; a homogeneous set of studies will result in this statistic equal to cero. Under the presence of heterogeneity this estimate should be different from cero. (4) It corresponds to the weighted average of coefficients reported in different estimations. The weights are calculated considering the sampling fluctuation of each effect size (standard error per reported coefficient) and estimated population variance of effect sizes (τ^2). ***,*** and * denote significance at the 1%,5% and 10%, respectively.

Appendix B: Meta-analysis techniques

Meta-analysis techniques are used when studies are not perfectly comparable, but evaluate the same or a closely related question. The main purpose of the meta-analysis is to exploit the information of a set of estimations for a specific problem. The techniques are especially used in medical sciences for summarising the effect of specific treatments or policies on a population of individuals. Each study commonly represents the unit of analysis, where a specific coefficient is estimated. Two approaches to meta-analysis can be used depending on the type of information employed and the population considered in the studies: fixed and random effects model.

A fixed effects approach can best under the presence of homogenous effect sizes, which implies a low level of variability in the estimated coefficients. The estimated effect of corresponds to the average of coefficients weighted by their respective standard deviation. For the meta-analysis presented in this paper, there are important sources of heterogeneity that prevent us from using a fixed effects approach. Heterogeneity in the individual country studies arises from the institutional and regulatory frameworks of credit provision as well as from the individual country characteristics. In this case, we opt for a random effects model, in which the objective is to try to model the unexplained heterogeneity of effects.

Random effects models conceptualise the population of effect sizes falling along a distribution with both mean and variance, but allows for variance due to sampling fluctuations of individual studies (Card (2016)). This type of estimation considers not only the level of variation for each specific estimated coefficient but also the level of variability of estimated coefficients among the studies. More formally, given a certain level of variability in the country effects, we could expect that the true effects of bank-specific characteristics on credit θ_i , varies between estimations by assuming that they have a normal distribution around a mean effect θ . We represent the effect the following way:

 $y_i | \theta_i \sim N(\theta_i, \sigma_i^2)$, with $\theta_i \sim N(\theta, \tau^2) \rightarrow y_i \sim N(\theta_i, \sigma_i^2 + \tau^2)$

Based on this approach, we estimate two sources of variance: (i) the variance around the mean of the estimated effect and (ii) the between-study variance. The main result of this estimation corresponds to a range where the expected value of the effect of certain bank characteristics on credit could be located.

To conduct a random effects meta-analysis we follow these steps:

- 1- Estimate the level of heterogeneity among effect sizes (Q statistic). The statistic is constructed using the squared weighted sum of the difference between the estimates and its average. Higher levels of the statistics denote high levels of heterogeneity. The statistical test rejects the null hypothesis of homogeneity under a χ^2 statistical distribution.
- 2- Calculate the magnitude of the level of heterogeneity in effect sizes (I² statistic). It is defined as the percentage of the residual variation that it is attributable to between study heterogeneity and calculated as the difference between the Q measure and the degrees of freedom divided by the Q measure. Levels of I² higher than 50% denote moderate to high levels of heterogeneity.

- 3- Estimate the population variability in effect sizes (τ^2). Under the presence of heterogeneity, this estimate should be different from zero.
- 4- Estimate the random effects mean. It corresponds to the weighted average of coefficients reported in different estimations. The weights are calculated considering the sampling fluctuation of each effect size (standard error per reported coefficient) and estimated population variance of effect sizes.