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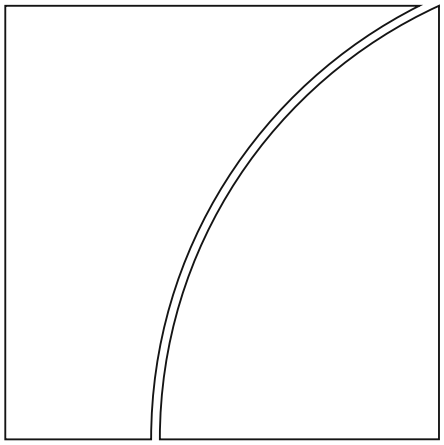

BIS Working Papers

No 798

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Monetary and Economic Department

July 2019

Paper produced as part of the BIS Consultative Council for the Americas (CCA) research project on "Changes in banks' business models and their impact on bank lending: an empirical analysis using credit registry data" implemented by a Working Group of the CCA Consultative Group of Directors of Financial Stability (CGDFS).

JEL classification: E51, E58, G21

Keywords: bank business models, bank lending, credit registry data, meta-analysis

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This publication is available on the BIS website (www.bis.org).

ISSN 1020-0959 (print)
ISSN 1682-7678 (online)

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

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Abstract

This paper focuses on the recent changes in banking systems and how bank-specific characteristics have affected credit supply in five Latin American countries (Brazil, Chile, Colombia, Mexico and Peru). We use detailed credit registry data and apply a common empirical strategy. Since data confidentiality prevents the pooling of the data, we use meta-analysis techniques to summarise the results. We find that large and well-capitalised banks with low risk indicators, stable sources of funding, and a commercial business model generally supply more credit. Such banks are also more sheltered from monetary and global shocks, with the role of specific characteristics varying by the type of shock.

Keywords: bank business models, bank lending, credit registry data, meta-analysis

JEL classification: E51, E58, G21

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1. Introduction

After the Great Financial Crisis (GFC), banks' activities and business models have undergone a transformation. Profound changes in money and securitisation markets and cross-border banking activity have modified bank funding structures. Technological innovation, including the use of artificial intelligence and machine learning models by fintech companies, has increased competition, affecting banks' traditional screening and monitoring activities, and transforming the business of lending. Together with the post-crisis regulatory response, these changes have had profound effects on how banks finance themselves and grant credit, ie on the "bank business models," and they are likely to affect how banks respond to monetary policy and external shocks. Several studies have focused on 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), Gambacorta et al (2019); CGFS (2018)). However, the effects on banks in emerging markets have been little investigated.

This paper investigates how the evolution of the banking systems of Latin America's main economies and their characteristics have affected the drivers of credit supply, including their response to shocks.[2] Lending accounts for the largest share of banks' assets. It is crucial for the financing of firms, especially in emerging markets where alternative forms of (market) funding are typically quite limited. The bank lending channel literature has largely focused on how bank characteristics can alter the transmission of monetary policy shocks to the supply of credit. We analyse in a more general way the role of bank characteristics in influencing the supply of credit. We do so in two respects. First, we consider the direct impact of characteristics on lending supply, analysing questions such as do well-capitalised banks supply more credit? Second, we look at how these characteristics affect how bank lending responds to shocks, analysing questions such as does the lending supply of well-capitalised banks reacts less sensitively to an external shock? Here we analyse the response of lending to domestic monetary policy shocks and four external shocks: global liquidity, economic policy uncertainty, commodity price shocks, and global financial uncertainty.

The paper focuses on five Latin American countries that maintain a credit registry database. This allows us to employ very granular data at the bank/firm-level to disentangle the drivers of credit supply from those of credit demand. Since we cannot pool the highly confidential data and run a single regression, the country analyses use a common methodology, adapted in some cases to take into account specific institutional details, to evaluate the effects of (changes in) bank characteristics on the supply of credit. Each country-team also contributed a narrative specific to their national experience. We then compiled the results obtained by each country and used meta-analysis techniques to summarise the findings.

[2] 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 BIS shareholder countries: Brazil, Chile, Colombia, Mexico and Peru.

Our main results are the following. First, we find that, in general and other things being equal, banks that supply more credit are large, well-capitalised, draw on more stable sources of funding, and have a *commercial bank* business model.[3] In contrast, banks supplying a lesser volume of loans have higher risk indicators, rely on volatile sources of funding, and have a *universal bank* business model.

Second, we find that the lending supply of well-capitalised and more profitable banks is less affected by monetary policy shocks, while those with high bank-risk indicators and a higher share of volatile sources of funding are more affected by these shocks. Bank-specific characteristics (BSCs) matter for banks' lending responses to global shocks. Banks with more capital, low risk indicators, and stable sources of funding are more apt to increase their credit supply during periods of high liquidity, while universal model banks take less advantage of the high liquidity conditions and increase their credit supply to a lesser degree. Generously capitalised banks with stable sources of funding are more sheltered against economic policy uncertainty shocks. By contrast, banks that rely on volatile sources of funding are more exposed to these shocks. Banks with low risk indicators and strong profitability are less apt to reduce their credit supply when hit by a commodity price shock. Finally, strongly capitalised banks with stable sources of funding are more sheltered against global financial uncertainty shocks, while universal model banks are more affected by such shocks.

The structure of the paper is as follows. In Section 2, we review the related literature. Section 3 then outlines the evolution of banking systems in Latin America after the GFC. Section 4 describes the empirical strategy implemented by each country. Section 5 presents, using meta-analysis techniques, the results obtained in the individual country papers. We first show how specific bank indicators (ie bank size, liquidity, capitalisation, revenue, funding and profitability) affect the supply of credit. Then, we show how these characteristics affect bank responses to monetary policy shocks and external shocks. Section 6 summarises the country-specific analyses. The last section concludes.

2. Related literature

Our paper builds on and contributes to the literature on how BSCs can strengthen or weaken the effects of monetary policy on the 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 total 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, low capitalisation and that are less able to raise uninsured funds.

[3] We differentiate between banks with a *commercial* and *universal* business model based on revenue indicators. Banks with a commercial business model have a higher share of net fees and commission income to operating income, retail loans to total loans, and broad credit to total assets. Banks with a universal business model have a higher share of non-interest income to total income, trading income to operating income, and assets held for trading to total assets.

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 only in "normal" liquidity conditions. Similarly, Altunbas et al (2010) find that bank risk plays an important role in assessing the effects of monetary policy on the loan supply. Banks with low risk indicators insulate better their loan supply from monetary policy changes since the have better prospects and easier access to uninsured fund raising. Finally, Gambacorta and Marques-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 that period.

Our second contribution is to the literature that examines the role of BSCs in sheltering banks from external shocks. 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 are 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.

Finally, we contribute to the literature that uses credit registry data to better identify credit demand and credit supply shifts. As noted, the confidentiality of credit registry data prevents us to combine it into a unique dataset. For this reason, we specify a common empirical approach, then compile and analyse the results using meta-analysis techniques. The empirical approach follows closely the work of Jimenez et al (2012). They use detailed data on loan applications from firms to analyse how reductions in credit availability due to adverse conditions depend on the strength of banks' balance sheets. 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. The main difference between their work and our empirical strategy is that we focus 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 studies have followed the same approach. One example is the initiatives undertaken by the International Banking Research Network (IBRN) summarised in Buch and Goldberg (2014). As part of the research conducted by eleven country-teams, the IBRN studies the

magnitude and mechanism for transmission of liquidity shocks through international banks. 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 affect bank-lending growth. They find that balance sheet conditions and business models drive the amplitude and direction of spillovers to lending growth rates. One last example is the research project developed by the BIS to study the impact of macroprudential policies on credit growth and their interaction with monetary policy. Gambacorta and Murcia (2019) present the results by five 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 BSC scan influence the impact of macroprudential policies on credit. For example, macroprudential polices had a greater effect on less stable financial institutions in Colombia and less strongly capitalized and liquid banks in Brazil.

3. Evolution of banking systems in Latin America after the GFC

This section analyses main trends in Latin America banking structures 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, regulatory responses to the crisis and 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.

First, monetary policy responses of Latin American countries lagged behind those of advanced economies during the GFC. Major advanced economies lowered almost immediately their monetary policy rates to near zero levels and long-term interest rates fell as well to historically low level. The response in Latin American countries was slightly different due to varying starting cyclical conditions and structural vulnerabilities. Central banks in the region did not ease monetary policy conditions until the global credit crunch started to affect domestic activity. Then, monetary authorities progressively lowered interest rates to historically low levels (Graph 1, left panel). Once the effects of the GFC started to dissipate, and faced with renewed inflationary pressures (Graph 1, centre panel), 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 (Graph 1, right panel).

Despite lower output growth in the post-crisis period, private sector credit and the size of banking systems have continued to expand in Latin America. Financial deepening, proxied by total credit to the private financial sector as a percentage of GDP, shows a rising trend (Graph 2, left panel). However, except for Chile, the levels are considerably lower than in advanced economies. The size of banking systems in Latin America shows a steady growth,

with banks' total assets to GDP increasing by 28 per cent on average during the last 10 years (Graph 2, centre panel). The number of banks in the region 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.[4]

The expansion of banking systems in Latin America has been accompanied by a rise in non-performing loans (NPL) ratio, a measure of bank risk. Before the GFC, banks around the world had low NPL ratios. After the GFC, the ratio increased in all advanced economies, reflecting rising risks in the global economy. However, by 2017 most advanced economies saw a decline in the NPL ratio below 1.5 percent, with the only exception being the Euro Area (CGDFS, 2018). In Latin America, the evolution of the NPL ratio is different depending on the country. However, a common observation for all countries is that the NPL ratio in 2017 was higher than in 2007, implying an overall increase in bank risk. In the last four years, the NPL ratio decreased in Chile and Mexico, while it rose in Brazil, Colombia, and Peru.

To reduce system-wide risks to financial stability, regulatory authorities strengthened banking regulation post-crisis. The main objective was to increase requirements for higher-quality capital and liquidity to increase the resilience of banking systems against shocks. 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 (CGDFS, 2018).

Another post-crisis change was the shift in funding composition of banks. Banks in advanced economies reduced their reliance on wholesale funding and increased 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 and their share in total liabilities is considerably higher than other sources of funding. However, greater access to international capital markets allowed Latin American banks to diversify their sources of funding and increase their share of long-term funding (Graph 3, right panel).[5]

Changes in cross-border bank claims on Latin American banks also affected their access to alternative sources of funding. Before the crisis, international banking activity grew faster than world economic activity and banking became increasingly global (McCauley et al, 2017). There was a sharp increase in bank claims on Latin American banks, which contracted upon the onset of the crisis (Graph 4, left panel). However, as international banks recovered so did the cross-border claims on Latin American banks, particularly from

[4] 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.

[5] An additional common trend in the region has been a reduction in the interbank borrowing and an increase in wholesale funding.

banks in the United States. Around 2012, the rising trend of bank claims started to flatten and, more recently, their volume has started to decrease. The inflow of securities has partially offset this decline, as banks and other corporations assessed international bond markets.

At the same time, there has been a higher presence of Latin American banks within its own region, especially from Colombian banks to Central America (Morales et al, 2019). This trend is in place also for emerging markets in other jurisdictions. Demirgüç-Kunt et al. (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.

Stricter regulation and the shift to more stable source of funding took a toll on bank profitability. 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). In Brazil and Mexico, there was a sharp decline in ROE during the crisis, which then recovered, albeit at a slower pace. In Chile, Colombia, and Peru the level of ROE has continuously decreased for the past decade.

Banks adjusted their business model as a response to the changes outlined above. Revenue composition can capture shifts in business models as it reflects 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, right 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 banking activities.

To complement our analysis, we classify banks in Latin America into trading, universal, and commercial business model to analyse how they have changed during the last decade.[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, while commercial banks have a low share of trading account securities and a substantial share of loans. Universal banks cover the middle ground.[7] We only consider banks that were present in the database throughout 2007 to 2017 to allow for proper comparison in changes in business models.

[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

After the GFC, there was a shift to more traditional commercial banking activities, but this trend reversed in the last five years (Graph 5). Banks transitioned from the trading and universal business model to the commercial business model from 2007 to 2012. During this period changes in funding and revenue strategies implied that 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. From 2012 to 2017, the number of commercial and universal banks increased while the number of trading banks increased. In terms of share of total assets, there was an increase in the share of universal banks and a reduction in the share of commercial and trading banks.

Banking systems in Latin America went through a profound transformation in the last decade. First, banks in the region have grown in size and have greater access to international capital markets. Second, regulatory responses in the aftermath of the GFC have strengthened banks' capital and liquidity positions. Third, bank profitability has been declining and bank risk has been increasing. Finally, banks have diversified their sources of funding and the type of activities they engage in, which has transformed banks' business models in the region. In the next section, we formally evaluate the impact of these changes on how banks grant credit and respond to monetary policy and external shocks.

4. Empirical strategy

This section describes the methodology implemented by each country-team to analyse how BSCs determine the supply of credit. First, we classify BSCs 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 or liquidity coverage ratio).
2. **Risk indicators:** loan-loss provisions as a share of total loans, share of non-performing loans, share of doubtful loans, and share of write-offs.
3. **Revenue mix (universal business model):** diversification ratio (non-interest income to total income), trading income as a share of operating income, assets held for trading as a share of total assets, and number of foreign subsidiaries.
4. **Revenue mix (commercial business model):** net fees and commission income as a share of operating income, retail loans as a share of total loans, broad credit to total assets.
5. **Stable sources of funding:** share of deposits over total liabilities, share of short-term funding, and 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), and number of employees per total assets.

The left side of Table 1 provides a summary of the indicators used by each country-team, which depended on data availability. The right side shows the expected signs of the relation between BSCs and lending growth and the bottom part of the table summarises the characteristics of each database.

Every country-team had access and used detailed credit registry data. The granularity of the data allows for the proper identification of the effects of BSCs on the credit supply, controlling for demand shifts. All countries used the same modelling strategy and data definition, as far as data sources allow in terms of coverage, collection methods and definitions, to allow for an international comparison.[8] We enhance the identification of the model by only considering firms that have loans with multiple banks. This implies a drop of the representativeness of the sample, but allows us to insert in the specifications both bank and firm*time fixed effects. The latter absorb time variant firm specific demand shocks (see Khwaja and Mian, 2008). We denote this sample as the multiple banking relationships (MBR) database.

For the second part of the analysis, we evaluate how BSC affect banks' response to shocks. We consider domestic monetary policy and global shocks. The monetary policy shocks are defined as the changes in the policy interest rate. We consider four additional external shocks (Graph 6).

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

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

We estimate the following panel equation to analyse how BSCs impact lending:[9]

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

The dependent variable $\Delta \log \text{Loan}_{f,b,t}$ is the change in the logarithm of outstanding loans by bank b to firm f at time t. $X_{b,t-1}$ is the vector of BSCs lagged one quarter; α_b denote time-invariant bank fixed effects and $\gamma_{f,t}$ correspond to time variant firm fixed effects. It is important to note that by including bank fixed effects we can interpret the coefficient estimates as variation within banks over time.

8 This approach has been followed by Buch and Goldberg (2014, 2017) and Gambacorta and Murcia (2019).

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

In a first step, each country-team ran individual regressions for each of the seven blocks of BSCs, as defined in the previous section. Then, the *baseline* specification includes those BSCs from each block that had a statistically significant coefficient in their individual regressions. This additional step is to reduce possible collinearity between the variables within each block of BSCs.[10]

We modify equation (1a) to conduct three robustness checks. First, we estimate the effect of BSCs on loan growth in the complete database (CD) controlling for macro and firm characteristics:

$$\Delta \log \text{Loan}_{f,b.t} = \beta X_{b,t-1} + \alpha_{f,b} + macro_t + firm_{f,t} + \varepsilon_{f,b,t} \quad (1b)$$

For the equation above, $\alpha_{f,b}$ correspond to time invariant bank-firm fixed effects; $macro_t$ is a vector of macroeconomic controls; and $firm_{f,t}$ a vector of firm controls.[11]

Second, we address the concern that the number of observations in the meta-analysis is too low (at least one from each country for every BSCs block). To this end, we perform a meta-analysis based on bank-level coefficients (β_b):

$$\Delta \log \text{Loan}_{f,b.t} = \beta_b X_{b,t-1} + \alpha_{f,b} + macro_t + firm_{f,t} + \varepsilon_{f,b,t} \quad (1c)$$

We required that each bank had observations for at least three years (one business cycle).

Finally, the last robustness check deals with the concern that a one-quarter lag could be too limited to rule out endogeneity between BSCs and lending growth. To address this issue, we estimate the effect on loan growth using a one-year lag (t-4) for each BSC:

$$\Delta \log \text{Loan}_{f,b.t} = \beta X_{b,t-4} + \alpha_b + \gamma_{f,t} + \varepsilon_{f,b,t} \quad (1d)$$

The coefficient of interest in all the equations is β, which characterises how BSCs determine shifts in the loan supply.

4.2 Bank-lending channel

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

$$\Delta \log \text{Loan}_{f,b,t} = \beta X_{b,t-1} + \sum_{j=0}^{3} \delta_j \left(\Delta \text{i}_{\text{t-j}} * X_{b,t-1}\right) + \alpha_b + \gamma_{f,t} + \varepsilon_{f,b,t} \quad (2a)$$

$$\Delta \log \text{Loan}_{f,b,t} = \beta X_{b,t-1} + \sum_{j=0}^{3} \delta_j \left(\Delta \text{i}_{\text{t-j}} * X_{b,t-1}\right) + \alpha_{f,b} + macro_t + firm_{f,t} + \varepsilon_{f,b,t} \quad (2b)$$

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

[11] Macroeconomic controls include growth in real GDP, change in current account deficit and depreciation of the exchange rate. Firm controls vary by country and depend on data availability.

We estimate equation (2a) with the MBR database. For robustness, we estimate equation (2b) with the complete database. In the equations above, 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 minimised the Akaike information criteria. Following the bank lending channel literature, we identify supply shifts to monetary policy shocks by means of the statistical significance of the coefficients in the vector δ_j.

4.3 Transmission of global shocks

The last part of the analysis evaluates which BSCs mitigate or exacerbate the impact of global factors/external conditions on the supply of credit. We write the model the following way:

$$\Delta \log \text{Loan}_{fbt} = \beta X_{b,t-1} + \lambda(D_{i,t} * X_{bt-1}) + \alpha_b + \gamma_{f,t} + \varepsilon_{fbt} \quad (3a)$$

$$\Delta \log \text{Loan}_{fbt} = \beta X_{b,t-1} + \lambda(D_{i,t} * X_{bt-1}) + \alpha_{f,b} + macro_t + firm_{f,t} + \varepsilon_{f,b,t} \quad (3b)$$

As in the previous models, we estimate equation (3a) with the MBR database and, for robustness, equation (3b) with the complete database. In this specification, $D_{i,t}$ corresponds to a dummy variable that characterises each of the four external shocks (high global liquidity, high economic policy uncertainty, low growth in commodity prices, and high global financial uncertainty). To calculate the dummy variables, we transform into percentiles each indicator used as proxy for the external shocks. Then, we identify extreme periods when the percentile values lie above a certain threshold (Graph 6, shaded area).[12] This part of the analysis focuses on how certain bank-specific characteristics can increase or reduce the sensitivity of the credit supply to global shocks (λ).

5. Summary of results using meta-analysis techniques

We estimate mean effects of BSCs on loan growth in Latin America by aggregating the results obtained from each country using meta-analysis techniques. We exploit the fact that all studies have the same design and the coefficients are comparable. In a meta-analysis, the objective is to obtain a single quantitative estimate by computing a weighted average across the studies' individual estimates

We apply a random effects model to conduct the meta-analysis. The key assumption is that the observed heterogeneity in the studies' estimates can be explained by two sources: the within-study sampling error and the between-study variance. The former arises because estimates within each study are imprecise. The latter can be attributed to differences between studies (eg differences in the institutional and regulatory frameworks, peculiarities of each country's banking system). These two variances are used to calculate the weight of each study's estimate in the mean effect (see Appendix A). The weight of

[12] Depending on sample availability of the database, country-teams adjusted the percentile to calculate the dummies.

coefficient reported in each study will be lower the larger the standard error of the estimate and the larger the estimated between-study variance.

We focus on the coefficients reported by each country-team for the three main equations in our empirical strategy. The set of coefficients of interest from equation (1a) are the ones associated with the BSCs (β).[13] For equation (2a), we focus on the coefficients of the interaction terms between BSCs and the monetary policy shock $\left(\sum_{j=0}^{3}\delta_j\right)$. Finally, the relevant coefficients in equation (3a) are related to the interaction terms between BSCs and global shocks (λ).

We summarise the results of the meta-analysis in Tables 2-7. Each table presents the estimated mean effect of the coefficients of interest with the MBR database and, for robustness, with the complete database. For the baseline, we also report the estimated mean effect using bank-level coefficients and a one-year lag for the BSCs. In the lower part of the tables, we report the percentage of variation that can be explained because of differences between studies rather than by imprecision of the estimates (I^2 statistic). Although there can be no absolute rule for when heterogeneity becomes important, Harbord and Higgins (2008) tentatively suggest that heterogeneity is substantial when I^2>75%.

We also present the results graphically in *forest plots*. The forest plot 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 it contributes to the estimated mean effect. A diamond marks the overall mean estimate and 95% confidence interval.

5.1 Effect of bank-specific characteristics on lending growth

The BSCs that have a positive and statistically significant mean effect on lending growth are size, capital, revenue indicators of commercial business models, and stable sources of funding. On the contrary, risk indicators, revenue indicators of universal business models, and volatile sources of funding have a negative and statistically significant mean effect on credit growth (Table 2, second row).

We graphically summarise the results in forest plots (Graphs 7-9). The rows correspond to the coefficient obtained for each country and the size of the blue squares represent the weights in the estimated mean effect. The x-axis represents the level of the coefficient, where red dots represent the country's results. The line that crosses each point represents the confidence interval. The red diamond represents the estimated 95% confidence interval of the estimated mean effect obtained with the MBR database.[14]

We focus on the analysis of BSCs that the majority of countries found have the same effect on the supply of credit. All country studies found that well-capitalised banks grant more

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

[14] For robustness, we also show the reported coefficients with the complete database (green dots) and the estimated mean effect (green diamond).

credit (Graph 7, right panel). 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 0.86 percentage points, with an estimated mean effect of 0.28 percentage points. This result is qualitatively similar to that obtained by Gambacorta and Shin (2018): a 1-percentage point increase in the equity-to-total-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 but one study found that banks with a high level of risk grant (ex-post) less credit (Graph 8, left panel). 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 0.33 percentage points.

Country studies found that a universal business model, other things being equal, is typically associated with a lower supply of credit (Graph 8, centre panel), while a commercial business model is associated with a higher supply of credit (Graph 8, right panel). Particularly, banks with a higher diversification ratio and trading assets to total assets in Mexico tend to grant less credit, while banks with a higher share of net fees and commissions income in Brazil and a higher share of retail loans in Chile tend to grant more credit.

Finally, the results show that the funding structure of banks is an important determinant of the credit supply. On the one hand, stable sources of funding have a positive impact on credit growth (Graph 9, left panel). There is a positive and statistically significant relation between the credit supply and banks with a higher share of short-term funding in Chile, higher deposits in Peru, and higher long-term funding in Mexico. On the other hand, volatile sources of funding have a negative impact on the loan supply (Graph 9, centre panel). There is a negative and statistically significant relation between credit growth and banks with a higher share of funding in foreign currency in Brazil and higher share of funding from foreign sources in Mexico.

We confirm our results by conducting three robustness checks. First, we compare the estimated mean effects with the MBR database to the estimates with the complete database (equation 1(b)). We find qualitatively similar results (Table 2, second and third row). There are more statistically significant estimated mean effects with the coefficients from the MBR database than from the complete database. The signs of the statistically significant mean effects from both databases are the same, except for the mean effect of liquidity on bank credit.[15] The measure of between study heterogeneity (I^2) tends to be higher for the estimates from the complete database (Table 2, fifth and sixth row). This can explained because data availability constraints prevented country-teams from introducing

[15] The mean effect of liquidity is the same as the reported coefficient from Mexico since the other reported coefficients are not statistically significant and have large standard errors (Graph 7, centre panel). This explains that the I^2 statistic is 0%. The country-team used the liquidity coverage ratio as their measure of bank liquidity. The authors argue that the negative sign of the coefficient of liquidity can explained by the challenges small banks faced in 2015 as they complied with the phase-in requirements of the Basel III liquidity coverage ratio. These banks increased their liquidity coverage ratio while granting less loans as they turned to long-term sources of funding and adjusted the maturity of their balance sheets. This effect is not present in the complete database.

the same firm controls in the regressions with the complete database, which increases the heterogeneity between studies.

Second, we address the concern that the number of observations in the meta-analysis is too low. To this end, we perform a meta-analysis based on bank-level coefficients (equation (1c)). Each country country-team obtained estimates of the effects of BSCs on loan growth individually for each bank. We confirm that the estimated mean effects calculated with the country-level coefficients are qualitatively similar to those calculated with the bank-level coefficients (Table 2, first and third row). We obtain more statistically significant results with the country-level coefficients, but the signs are the same in both mean estimates.[16] The percentage of residual variation attributable to between-study heterogeneity (I^2 statistics) is in most cases higher with the bank-level estimates (Table 2, fifth and seventh row). We expect a higher heterogeneity since we are taking into account sources of variability between banks in addition to between countries.

The third robustness check deals with the concern that a one-quarter lag could be too limited to rule out endogeneity issues between BSCs and lending growth. To address this issue, each country-team obtained estimates of the effects of BSCs on loan growth using a one-year lag (t-4) for each BSC (equation (1d)). The estimated one-year lag mean effects of BSCs on credit growth are compatible with the estimated one-quarter lag mean effects (Table 2, first and fourth row). We lose statistical significance for some mean-effects but the signs are consistent.[17] We can also interpret these results as the one-year effect of changes in BSCs on the credit supply. We find that a reduction in bank risk and an increase in the bank capital ratio and stable sources of funding have a positive effect on credit growth after one year. The result imply that changes in these variables have strong persistent effects on the supply of credit. Even more, the mean effect of stable sources of funding is greater one-year after compared to one-quarter after. This implies that a higher share of stable sources of funding has a compounding effect that affects positively the credit supply of banks.

5.2 How banks with different characteristics react to monetary policy shocks

We now analyse how BSCs affect the reaction of bank lending to monetary policy shocks (Table 3, first row). The estimated mean effect of the interaction between capital and the monetary policy shock is positive and significant (Graph 10, first panel). Additionally, all country studies reported that the interaction term had a positive sign. This well-established result in the bank-lending channel literature implies that banks with higher capital are less affected by monetary policy shocks.

Next, we find that banks with a high level of risk and that rely on volatile sources of funding contract more their credit supply if there is a tightening in monetary policy (Graph 10, second and third panel). The intuition is that, during a tightening of monetary conditions, banks that appear to have more risk, either in their loan portfolio or in their funding

[16] The exception is the estimated mean effect of liquidity on credit growth. As mentioned before, the estimates from Mexico drove the mean effect estimated with country-level coefficients. Using bank-level coefficients, we find that the effect is positive and statistically significant. In this case, the weights of the coefficients were more evenly distributed across banks. This last result is consistent with the literature on the effect of bank liquidity ratio on the credit supply.

[17] The exception is the sign of the mean effect of size on loan growth. However, the mean effect is not significant.

composition, find it more difficult to raise additional funds, thereby reducing more their loan supply. On the contrary, we find that, banks that are more profitable are less affected by monetary policy shocks (Graph 10, fourth panel). Banks with higher profitability indicators are better able to obtain additional funds during a monetary tightening and reduce less their credit supply.

For robustness, we compare the estimated mean effects obtained with the MBR database to those obtained with the complete database (Table 3, first and second row). As with the baseline results, we lose some significance but all the signs remain the same. [18] Additionally, in most cases there is a higher degree of heterogeneity (I^2) for the estimate with the complete database compared to the MBR database.

5.3 How banks with different characteristics react to global shocks

In this section, we analyse how banks with different characteristics react to global shocks. Table 4 presents the results of the interaction term between BSCs and the global liquidity shock (dummy for periods of negative Federal Funds shadow rate). In general, well-capitalised banks, with low risk indicators and stable sources of funding are more apt to increase their credit supply during periods of high liquidity (Graph 11, first, second and third panel). On the contrary, universal model banks take less advantage of the high liquidity conditions and increase their credit supply to a lesser degree (Graph 11, fourth panel). The results with the complete database are similar.

After the GFC, there was a period with excess liquidity in the market fuelled by accommodative monetary policies in advanced economies. The results imply that the increase in the credit supply in Latin America was mainly driven by banks with high capital, liquidity, and that rely on stable sources of funding.

Table 5 shows the results for the global economic policy uncertainty shock (dummy for periods of high Baker, Bloom and Davis (2016) index). In general, banks with higher capital and stable sources of funding are more sheltered against these shocks (Graph 12, left and centre panel). Differently from the previous exercises, we find an additional statistical result with the complete database: banks that rely on volatile sources of funding are more affected by economic policy uncertainty (Graph 13, right panel). During the GFC, banks that relied heavily on volatile sources of funding, such as wholesale funding, were among the ones more affected by the funding crunch. The results show that the funding structure of banks is relevant not only to shelter against monetary policy shocks but also against economic policy uncertainty.

Table 6 summarises the results for the commodity price shock (dummy for period of low growth in commodity prices). In this case, we find consistent signs between both databases but different statistical significance. With the MBR database, banks with higher risk reduce more their credit supply when faced with lower commodity prices (Graph 13, left panel). With the complete database, banks with high profitability are less affected by these shocks

[18] The mean estimate of the interaction between liquidity and the monetary policy shock is positive and significant for the complete database. However, 90% of the weight is assigned to the coefficient reported by Mexico. No other reported coefficients of the interaction term between liquidity and the shock are statistically significant.

(Graph 14, right panel).[19] These results are particularly relevant since the majority of countries considered in the sample are commodity exporters.

Finally, table 7 presents the results for the global risk shock (dummy for periods of high VIX). With the MBR database, we do not find any statistically significant results. However, we find some interesting outcomes with the complete database. In general, banks with high levels of capital and stable sources of funding are more sheltered against risk shocks, while banks with a high level of risk are more affected by these shocks (Graph 14). One of the main targets of the post-crisis regulation was to increase banks' capital buffers and to shift the composition of their funding towards more stable sources. The results imply that one benefit of the post-crisis regulation will be higher resilience of Latin American banks against risk shocks.

6. Summary of country papers

Country studies corroborated the above results taking into account specific institutional details in each jurisdiction. We summarise below some additional results from the country papers.

Brazil. Barbone (2019) estimates the real effects of monetary policy surprises in Brazil. The identification of monetary surprises is through high-frequency data of changes in interest rate derivatives. He finds a strong lending channel operating mostly through bank capital. Firms connected to weaker banks face stronger negative shocks that translate into a sharp decline in credit and employment. Conversely, firms connected to stronger banks alleviate about one third of these effects on credit and two-thirds on employment.

Chile. Birón, Córdova and Lemus (2019) focus on the relevance of the state-owned bank (Banco Estado) on the Chilean banking system. First, Banco Estado helped the quick recovery of the Chilean economy after the GFC. During the crisis, Banco Estado was capitalised by the government, which allowed the bank to operate counter-cyclically and grant more loans while the remaining banks reduced their credit supply. Second, they find that the behaviour of Banco Estado is less cyclical than that of the rest of the banks. Finally, they show that Banco Estado behaves counter-cyclically during commodity price shocks. They conclude that Banco Estado plays a useful role in stabilising credit over the business cycle.

Colombia. Morales, Osorio and Lemus (2019) evaluate whether the strength of the credit channel has changed in Colombia because of the expansion of domestic banks abroad, mainly to Central America. They find that the internationalisation of domestic banks in Colombia plays a cushioning role in the financial system against changes in monetary policy. They show that during a monetary tightening international banks switch strongly from domestic to foreign sources of funding. Then, as domestic funding becomes relatively more available to purely local banks, their response to the shock is not statistically different

[19] For the complete database, the estimated mean effect of the interaction term between revenue indicators of commercial business models and the shock is positive and significant. However, this result is driven by the reported coefficient of Mexico. None other coefficient was reported significant.

from that of international banks. However, the cost of credit from purely domestic banks is slightly higher.

Mexico. Cantú, Lobato, López and López-Gallo (2019) find that foreign subsidiaries in Mexico contract more their loan supply when hit by global shocks compared to domestic banks. Foreign subsidiaries hold 65% of the share of total assets in the Mexican banking system. They also find that some bank characteristics (a universal business model, higher share of funding from foreign sources, and lower share of deposits) that strengthen the transmission of shocks for domestic banks weaken the transmission of shocks for foreign subsidiaries. Additionally, they show that low-risk firms with strong banking relationships are more sheltered against shocks. Finally, while high banking system concentration in Mexico (7 banks own 80% of total assets) deters loan growth, it shelters the system against external shocks.

Peru. Bustamante, Cuba, and Nivin (2019) analyse how BSCs affect the supply of domestic and foreign currency credit. For the latter, they find that banks that are well-capitalised, profitable, more diversified, and have a greater share of deposits and NPLs grant more credit in foreign currency. Additionally, they show that reserve requirements, both in domestic and foreign currency, are effective in curbing domestic credit in Peru. Finally, they find that the impact of negative commodity price changes on bank lending is difficult to contain even for strong banks, reflecting the dependency of the economy to the commodity cycle.

7. Conclusions

Banking systems are changing in response to post-crisis regulation, a new economic environment and the effects of financial innovation. These changes affect how banks are funded and on how they operate. Several studies have focused on the effects of changes in banks' business models after the crisis in advanced economies. But the effects on the banking systems of emerging markets have so far been less investigated.

In this paper, we analyse how the evolution of the banking systems of the main Latin American economies together with bank characteristics have affected credit supply, including how supply responds to shocks. It is hard to identify the effect of changes and shocks on lending supply because these can also affect the demand side. However, the use of micro data allows for a more precise disentanglement of loan demand and supply movements. Our focus is on five Latin American countries that maintain a credit registry database. As it was not possible to pool the highly confidential data in one database and run a panel regression, all country-teams used a common methodology to evaluate the effects of (changes in) bank characteristics (or business models) and shocks on the supply of credit. We then compiled the results obtained by each country and summarised them using meta-analysis techniques.

The main results are, first, big and well-capitalised banks and those with low risk indicators, stable sources of funding, and a commercial business model, generally supply more credit. Second, consistent with the bank lending channel literature, banks with high capital, low risk indicators, high profitability and a lower share of volatile sources of funding adjust

their credit supply less when faced with a monetary shock. Third, bank-specific characteristics also matter for banks' lending responses to global shocks. Strongly capitalised banks with stable sources of funding are more sheltered against global financial uncertainty shocks and economic policy uncertainty shocks. Universal model banks are more affected by global financial uncertainty shocks, while banks with a higher share of volatile funding sources are more affected by economic policy uncertainty shocks. Finally, banks with low risk indicators and high profitability reduce their credit supply less when hit by a commodity price shock.

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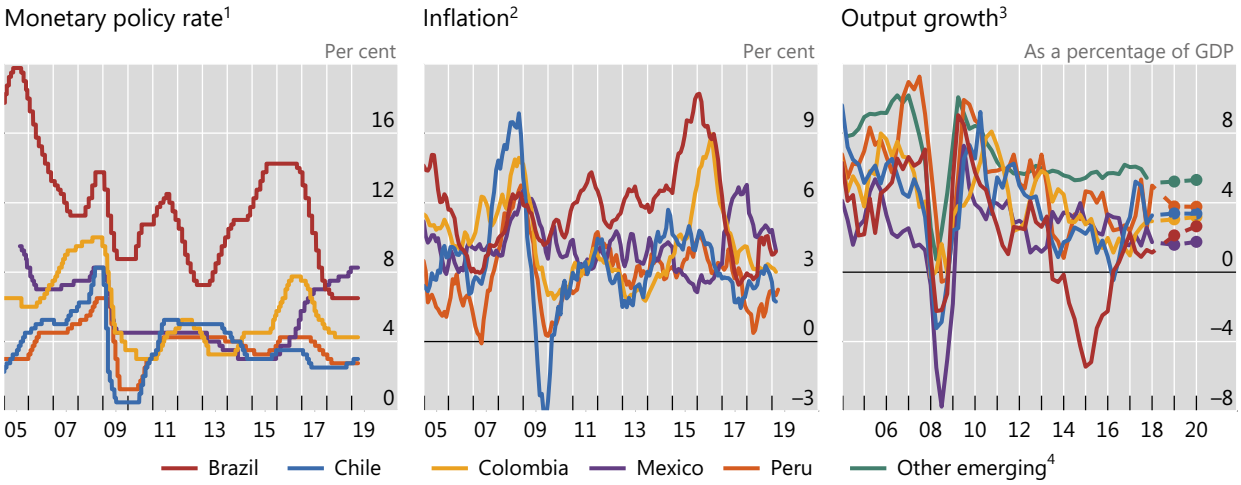
Graphs and Tables

Economic outlook in Latin America

Graph 1

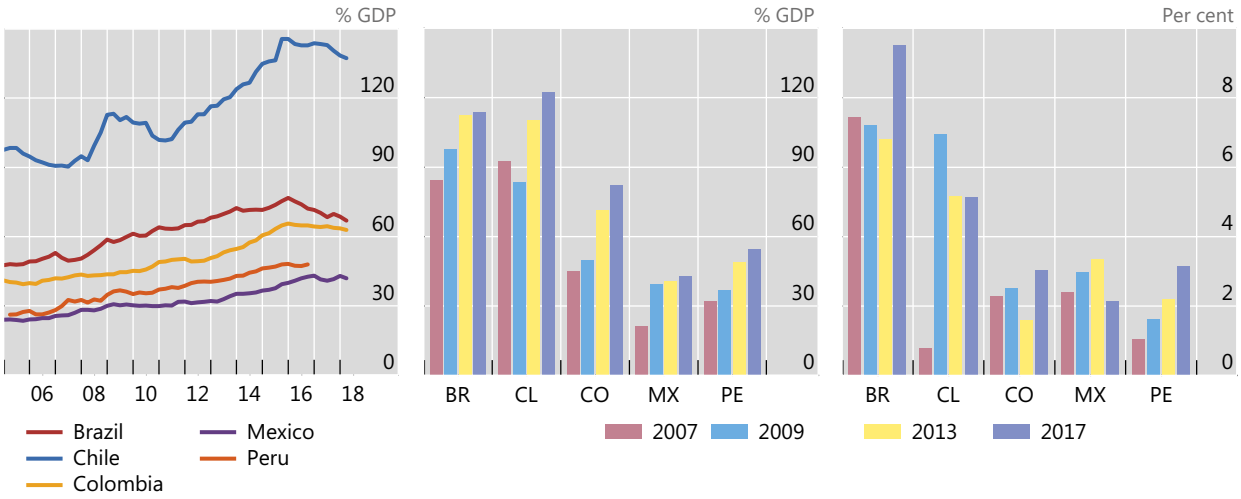


[1] For Brazil, target for SELIC overnight rate; for Chile, monetary policy rate; for Colombia, expansion minimum intervention rate; for Mexico, overnight policy rate (prior to 2008, bank funding rate); for Peru, reference rate. [2] Year-on-year changes in consumer price index. [3] Forecast shown as 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; Consensus Forecast; Datastream; OECD; national sources;

Banking systems in Latin America

Graph 2

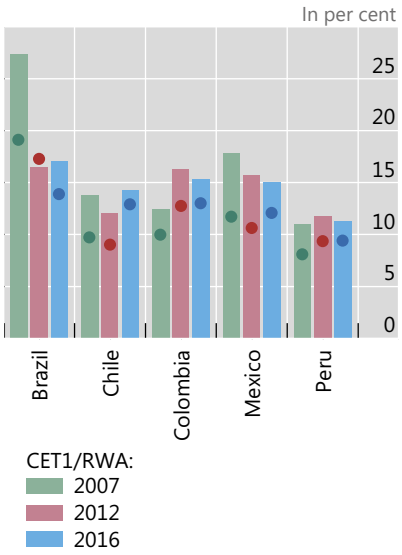


Source: Fitch Connect; BIS statistics.

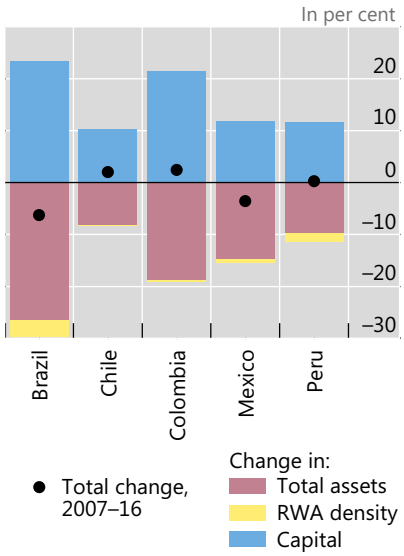
Bank capitalisation and funding structure

Graph 3

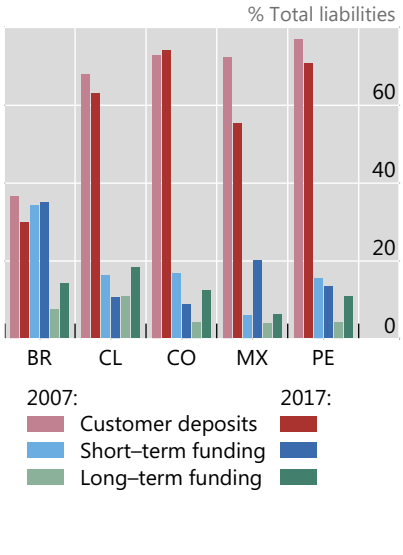
Capital ratios[1,2]



Capital adjustment strategies[3]



Funding shares



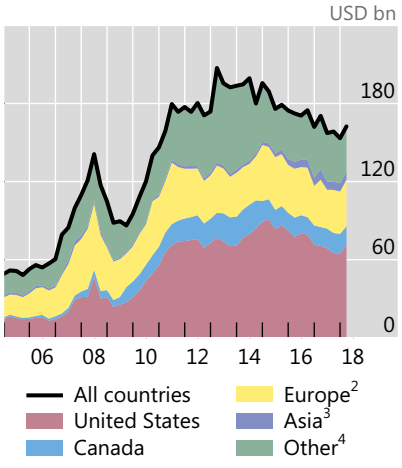
[1] Median ratios. [2] For Brazil data in 2016 corresponds to data in 2015. For Peru data in 2007 corresponds to data in 2009. [3] Decomposes the change in the Common Equity Tier 1 (CET1) capital ratio into additive components. The total change in the ratios is indicated by dots. The contribution of 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.

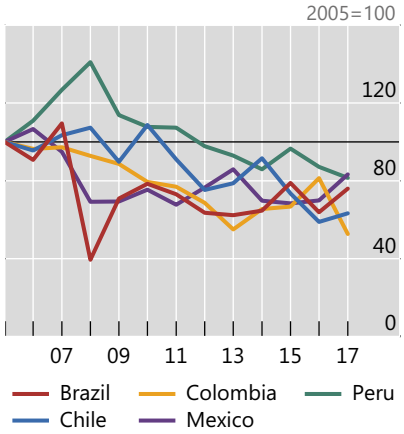
Foreign funding, profitability, and revenue

Graph 4

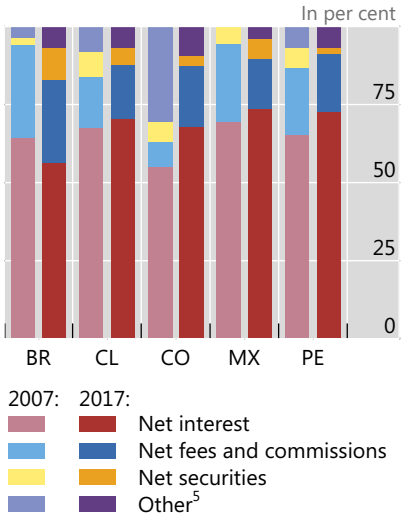
Bank claims on Latin American banks[1]



Return on equity



Revenue composition

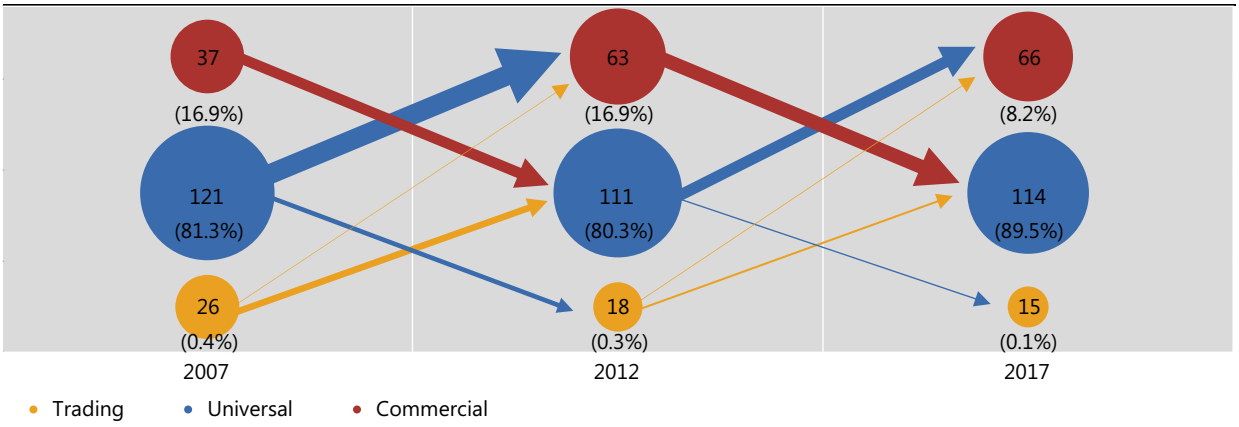


[1] Outstanding cross-border bank claims of reporting banks on Brazil, Chile, Colombia, Mexico and Peru. Claims include bank loans and other instruments except banks' holding of debt securities. [2] Austria, Belgium, Denmark, France, Finland, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, 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.

Transition across bank business models in Latin America

Number of banks; percent of total assets in parenthesis[1] Graph 5

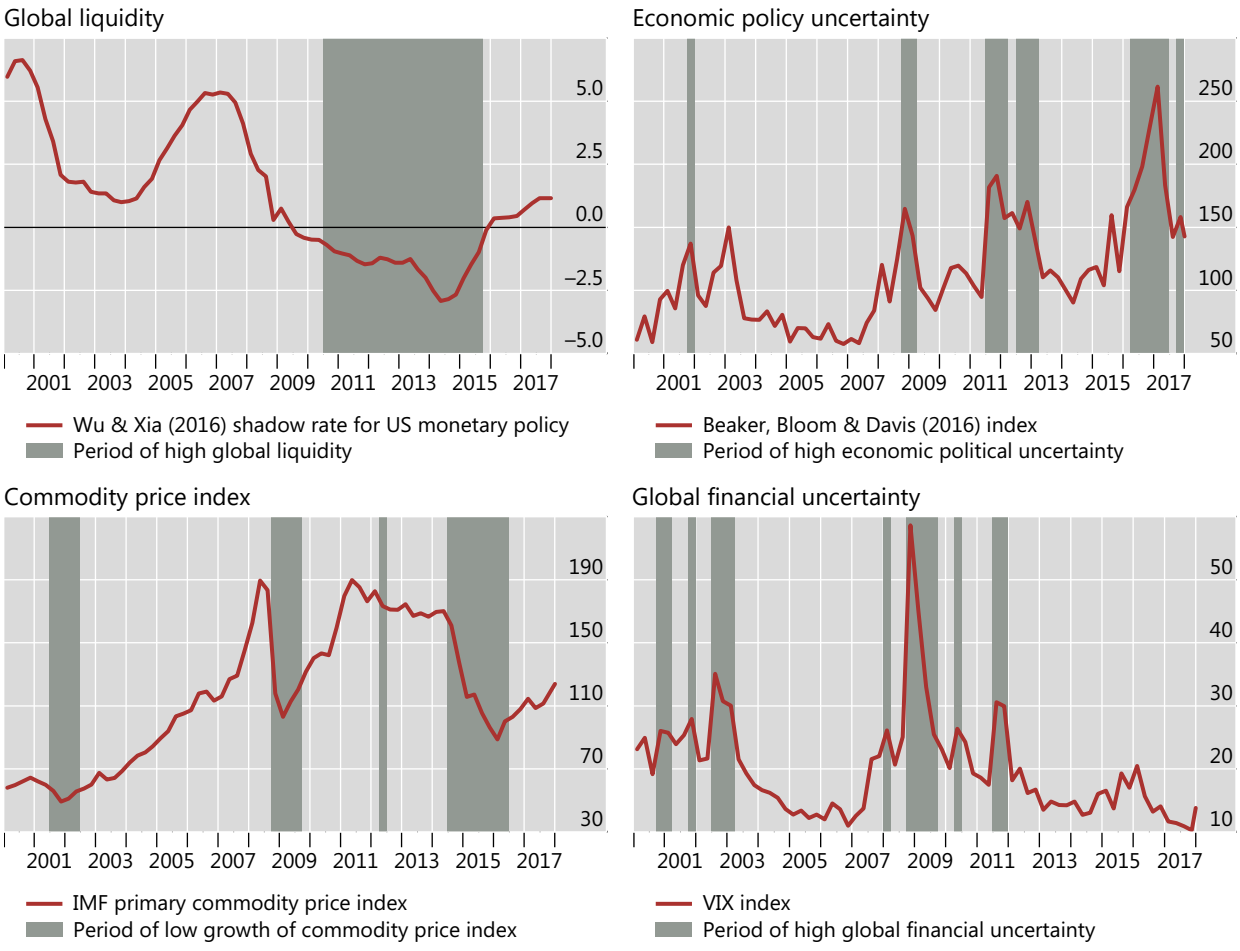


[1] Percentages do not add up to 100% since there are banks without classification.

Source: Fitch Connect.

Global shocks

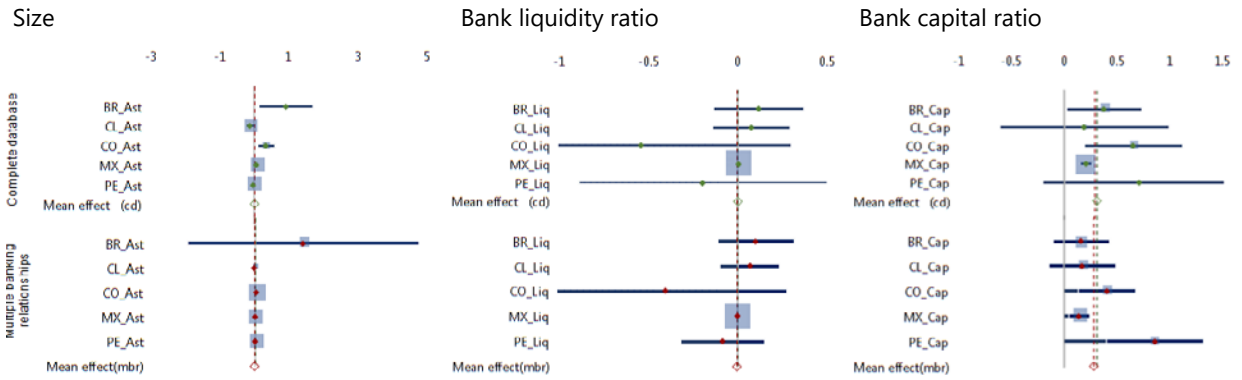
Graph 6



Source: Datastream; IMF; Wu and Xia (2016), Baker, Bloom & Davis. (2016).

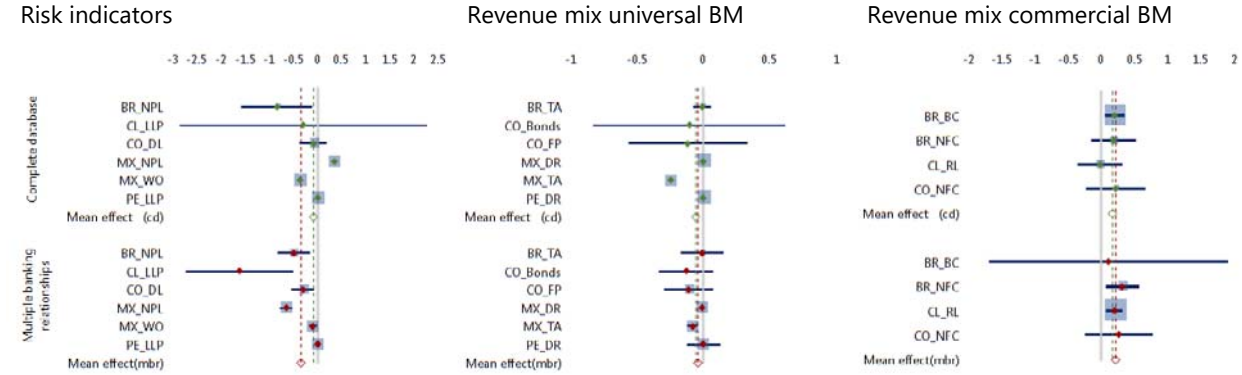
Effect of banks' size, liquidity, and capital on lending growth

Graph 7



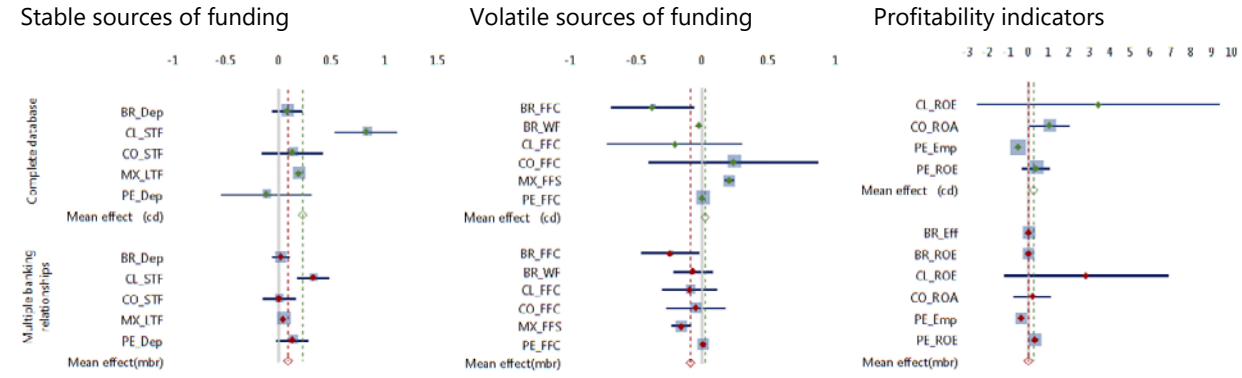
Effect of banks' risk and revenue indicators on lending growth

Graph 8



Effect of banks' sources of funding and profitability on lending growth

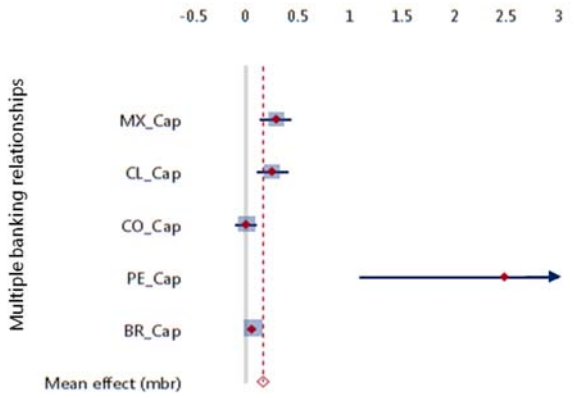
Graph 9



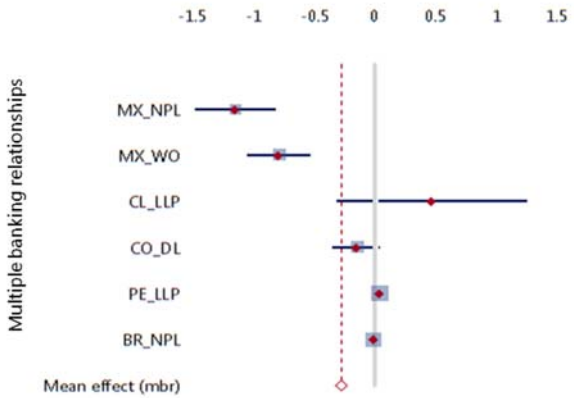
Notes: The rows correspond to the coefficient obtained by each country and the size of the blue squares represent their weights in the estimated mean effect. The weight is calculated as the inverse of the estimate's standard error, as reported in the underlying study, plus the estimated between-study variance. The x-axis represents the level of the coefficient, where green dots represent the country's results from the complete database and red dots from the MBR database. The line that crosses each point represents the confidence interval of the estimated value. The green/red diamond represents the estimated 95% confidence interval of the estimated mean effect obtained from the CD/MBR database. For details on the abbreviations, refer to Table 1.

How banks with different characteristics react to monetary policy shock Graph 10

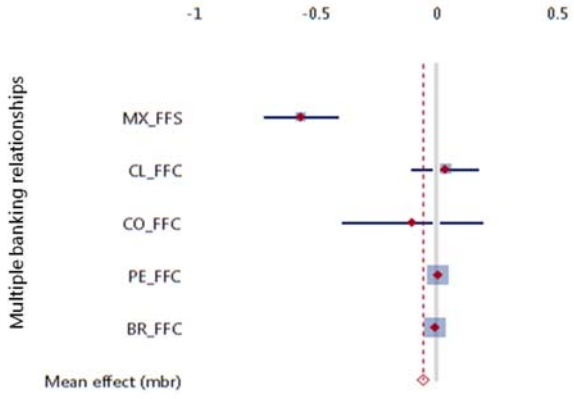
Bank capital ratio



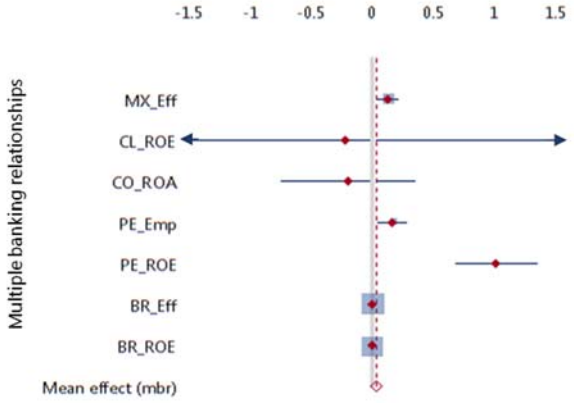
Risk indicators



Volatile sources of funding



Profitability



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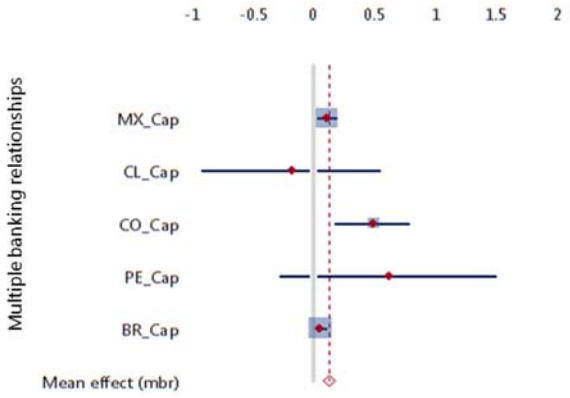
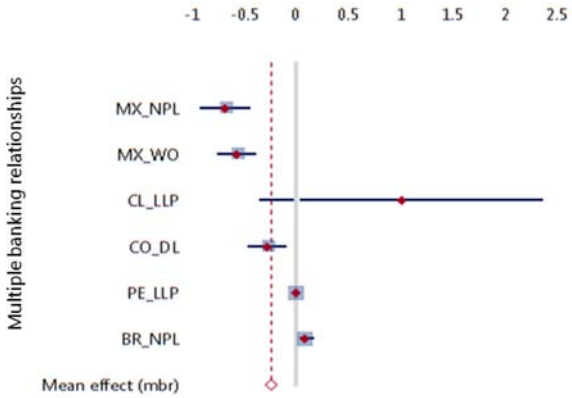
How banks with different characteristics react to global liquidity shocks

Graph 11

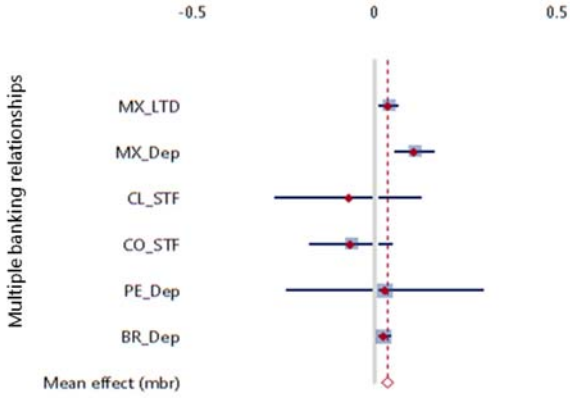
Bank capital ratio



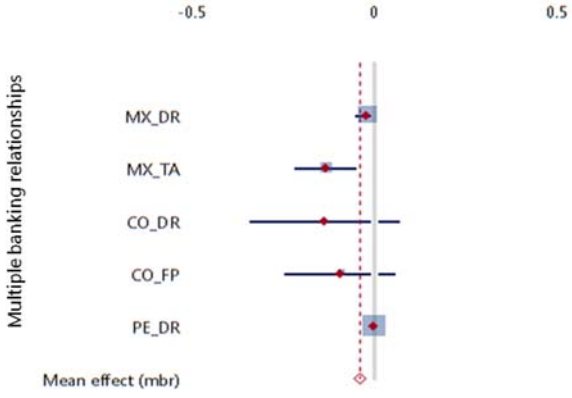
Risk indicators



Stable sources of funding



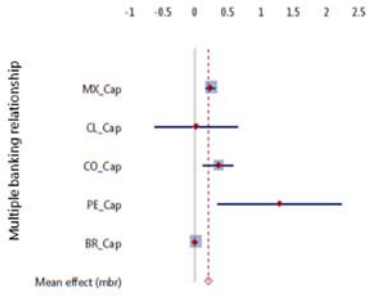
Revenue universal BM



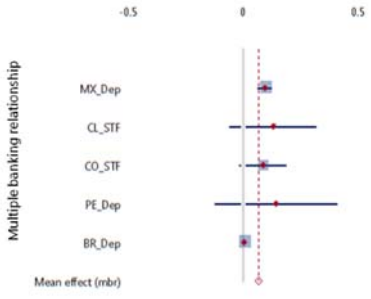
How banks with different characteristics react to economic policy uncertainty

Graph 12

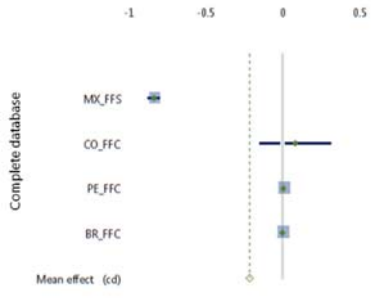
Bank capital ratio



Stable sources of funding



Volatile sources of funding

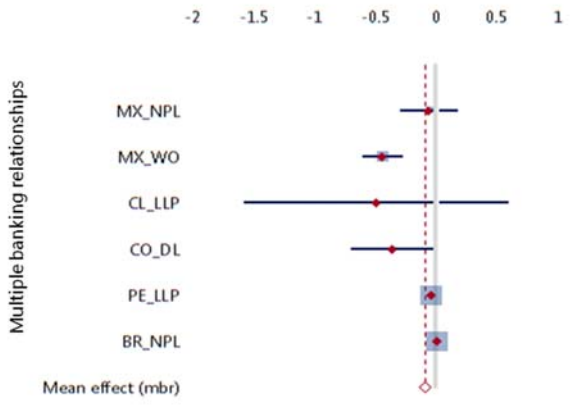


Notes: The rows correspond to the coefficient obtained by each country and the size of the blue squares represent their weights in the estimated mean effect. The weight is calculated as the inverse of the estimate's standard error, as reported in the underlying study, plus the estimated between-study variance. The x-axis represents the level of the coefficient, where green dots represent the country's results from the complete database and red dots from the MBR database. The line that crosses each point represents the confidence interval of the estimated value. The green/red diamond represents the estimated 95% confidence interval of the estimated mean effect obtained from the CD/MBR database. For details on the abbreviations, refer to Table 1.

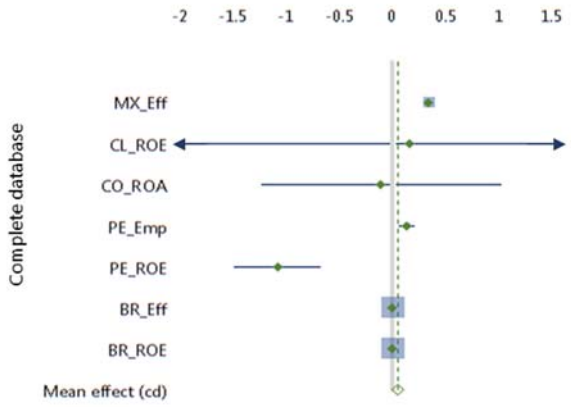
How banks with different characteristics react to commodity price shocks

Graph 13

Risk indicators



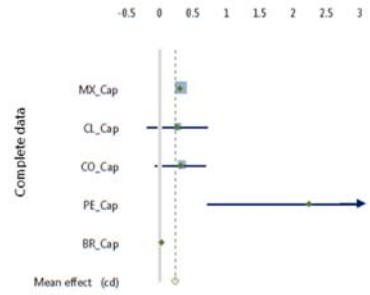
Profitability



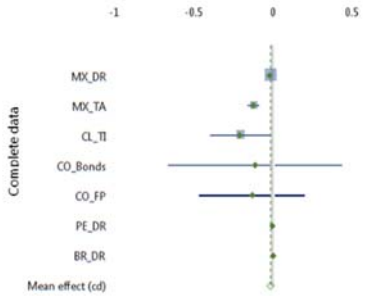
How banks with different characteristics react to global uncertainty shocks

Graph 14

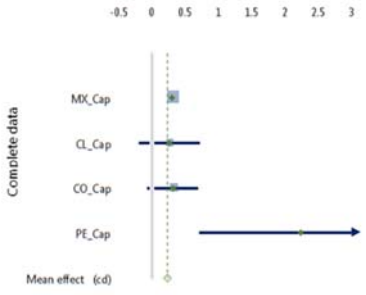
Bank capital ratio



Revenue universal BM



Stable sources of funding



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Bank specific characteristics used in the analysis by each country

Table 1

Variable Name	Abbrv.	Expected Sign	Basic Argument	BR	CL	CO	MX	PE
Main indicators								
ln (total assets)	Ast	+/ -	Large banks might isolate better adverse shocks (+). In case of interal capital markets or strong lending relationship between small firms and small banks (-).	X	X	X	X	X
Bank capital ratio	Cap	+	Well-capitalised banks more likely to expand supply of loans.	X	X	X	X	X
Bank liquidity ratio	Liq	+	Highly-liquid banks more likely to expand supply of loans.	X	X	X	X	X
Risk indicators								
Loan-loss provisions as a share of total loans	LLP	+/ -	Depending on the regulation reagrding levels of loan-loss provision, it can either signal high risk (-) or the strength of banks against losses (+).		X	X		X
Non-performing loans as a share of total loans	NPL	+/ -	Riskier banks might expand lending by more, especially versus risky segments (+). Alternatively if forced by regulation to contain their credit portfolio (-).	X			X	
Doubtful loans as a share of total loans	DL	-	As the share of doubtful loans and write-offs increases, repayment of loans starts to be an issue. Banks will			X		
Write-offs as a share of total loans	WO	-	be less able to raise additional funds, which would affect negatively the credit supply.				X	
Revenue mix (Universal Business								
Diversification ratio	DR	-	Banks with more diversified operations will lend less as they rely more on alternative sources of income.	X			X	X
Share of trading income	TI	-		X	X			
Assets held for trading as a share of total	TA	-				X	X	
Number of foreign subsidiaries	FP	-	Banks with a greater number of foreign subsidiares are more vulnerable to shocks in host countries.					
Revenue mix (Commercial Business								
Share of net fees and commission income	NFC	+	Banks with a more traditional business model that rely on interest income, fees and comimssions lend more.	X	X	X		
Retail loans as a share of total loans	RL	+			X			
Broad credit to total assets	BC	+		X				
Stable sources of funding								
Shares of deposits over total liabilities	Dep	+	Banks with more deposti funding (stable) could expand more the supply of loans.	X			X	X
Share of short-term funding	STF	+/ -	Banks with more short-term funding are more subject to market conditions.		X	X		
Share of long-term funding	LTF	+	Long-term sources of funding imply less risk, allowing banks to grant more loans.				X	
Volatile sources of funding								
Wholesale funding ratio	WF	-	Banks with more wholesale funding are more subject to market conditions.	X				
Share of funding in foreign currency	FFC	-	High dependance on foreign sources of funding and high share of funding in foreign currency increases the	X	X	X		X
Share of funding from foreign sources	FFS	-	vulnerability of banks against the exchange rate and volatile capital flows, which would reduce lending.				X	
Profitability								
Efficiency ratio	Eff	+	More profitable and efficient banks are more likely to expand their credit supply.	X			X	
Number of employees per total assets	Emp	+						X
ROE	ROE	+		X				X
ROA	ROA	+			X	X		
Database characteristics								
Number of debtors				118,639	104,109	35,055	112,905	4,182
Number of banks				96	36	33	42	18
Time period				2004Q1-2016Q4	2000Q1-2016Q4	2007Q1-2017Q2	2009Q4-2017Q4	2004Q1-2015Q4
Observations				3,991,769	4,629,902.00	2,938,279	2,661,018.00	1,768,213.00

Effect of bank-specific characteristics on lending growth

Table 2

	Size	Bank capital ratio	Bank liquidity ratio	Risk indicators	Revenue commercial BM	Revenue universal BM	Stable sources of funding	Volatile sources of funding	Profitability
Mean effect:									
MBR	**0.0147***	**0.28*****	**-0.004*****	**-0.333*****	**0.2211*****	**-0.0273***	**0.0885****	**-0.0891***	0.0142
CD	0.0184	**0.31*****	**0.0019*****	-0.0813	**0.1747*****	**-0.057*****	**0.2255****	0.0235	0.2871
Banks	**0.22*****	**0.66*****	**0.046*****	**-0.1046****	0.0181	**-0.0124****	0.0625	**-0.1773*****	0.5909
MBR_{t-4}	0.0079	**0.1534***	0.0552	**-0.2025****	0.0575	-0.0013	**0.1781****	-0.0151	0.0079
Percentage of between-study heterogeneity (I^2):									
MBR	49.00	65.42	0.00	**95.04**	0.00	51.89	70.66	**78.74**	**91.44**
CD	**96.32**	29.03	0.00	**98.99**	0.00	**98.7**3	**81.48**	**95.59**	**80.38**
Banks	**97.44**	**94.46**	**95.05**	**92.35**	**93.52**	**95.95**	**95.30**	**97.48**	**87.42**
MBR_{t-4}	**90.45**	42.97	58.05	**89.87**	**79.70**	40.15	**92.22**	**88.27**	**83.49**
Observations:									
Country level	5	5	5	6	4	6	5	6	5
Bank level	133	139	141	156	141	153	172	166	54

How banks with different characteristics react to monetary policy shocks

Table 3

	Size	Bank capital ratio	Bank liquidity ratio	Risk indicators	Revenue commercial BM	Revenue universal BM	Stable sources of funding	Volatile sources of funding	Profitability
Mean effect:									
MBR	0.0013	**0.165****	0.0108	**-0.271*****	0.0038	-0.0012	0.0585	**-0.0555***	**0.0379***
CD	0.003	0.0404	0.0144***	-0.1186	0.0743	-0.0221	0.0132	-0.2009	**0.2586***
Percentage of heterogeneity (I^2):									
MBR	53.62	**81.50**	**78.28**	**93.57**	0.00	**85.67**	**89.61**	**91.11**	**85.33**
CD	71.00	**93.15**	4.96	**99.25**	**97.59**	**98.63**	**86.53**	**98.47**	**76.57**
Observations	5	5	5	6	4	4	5	5	7

Notes: MBR corresponds to the estimates with the multiple-banking relationships database, CD to the complete database, Banks to the bank-level regressions, and MBR_{t-4} to the one-year lag regressions. The mean effect 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 between-study variance. The I^2 statistic is 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. Although there can be no absolute rule for when heterogeneity becomes important, Harbor and Higgins (2008) tentatively suggest adjectives of low for I^2 values between 25% and 50%, moderate for 50%-75% and high for values larger than 75% (in bold). ***,** and * denote significance at the 1%,5% and 10%, respectively.

How banks with different characteristics react to global liquidity shocks

Table 4

	Size	Bank capital ratio	Bank liquidity ratio	Risk indicators	Revenue commercial BM	Revenue universal BM	Stable sources of funding	Volatile sources of funding	Profitability
Mean effect:									
MBR	0.0079	**0.1287***	0.0275	**-0.2366****	0.003	**-0.0405***	**0.0342***	0.0347	0.0188
CD	0.0006	**0.210****	0.0173	**-0.2197****	0.005	-0.0147	0.0054	0.0098	0.0349
Percentage of heterogeneity (I^2):									
MBR	60.25	47.19	**80.56**	**91.66**	0.00	63.52	46.01	**78.32**	69.30
CD	72.72	**78.99**	7.58	**94.23**	0.00	**90.80**	**91.21**	45.70	71.97
Observations	5	5	5	5 (CD) 6 (MBR)	3	4 (CD) 5 (MBR)	6	5	6

How banks with different characteristics react to eco. policy uncertainty

Table 5

	Size	Bank capital ratio	Bank liquidity ratio	Risk indicators	Revenue commercial BM	Revenue universal BM	Stable sources of funding	Volatile sources of funding	Profitability
Mean effect:									
MBR	0.001	**0.2027***	0.0021	-0.0173	0.0081	-0.0023	**0.0648***	-0.0024	0.0782
CD	0.0013	0.0751	0.0006	-0.6316	0.0672	-0.0035	**0.1386****	**-0.2136*****	0.1816
Percentage of heterogeneity (I^2):									
MBR	54.08	**86.45**	29.48	**84.28**	63.94	**77.80**	**82.57**	**76.19**	58.79
CD	**89.73**	**84.15**	0.00	**88.71**	**99.12**	**88.48**	52.37	**99.64**	**86.60**
Observations	5	5	5	3(CD) 4 (MBR)	4 (CD) 5 (MBR)	5	4 (CD) 5 (MBR)	4	4

How banks with different characteristics react to commodity price shocks

Table 6

	Size	Bank capital ratio	Bank liquidity ratio	Risk indicators	Revenue commercial BM	Revenue universal BM	Stable sources of funding	Volatile sources of funding	Profitability
Mean effect:									
MBR	0.0073	0.0854	0.0048	**-0.0845****	0.001	-0.0156	0.0505	-0.0023	0.0007
CD	0.0013	0.1737	0.0055	-0.0591	0.071***	-0.026	0.0318	-0.1462	**0.0473*****
Percentage of heterogeneity (I^2):									
MBR	31.87	61.92	**83.36**	**84.23**	0.00	50.59	**90.26**	**93.63**	**86.37**
CD	52.67	**97.71**	65.06	**94.43**	0.00	**94.35**	0.00	**98.70**	**96.51**
Observations	5	5	5	5 (CD) 6 (MBR)	4	5	5 (CD) 6 (MBR)	4 (CD) 5 (MBR)	7

Notes: MBR corresponds to the estimates with the multiple-banking relationships database and CD to the complete database, The mean effect 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 between-study variance. The I^2 statistic is 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. Although there can be no absolute rule for when heterogeneity becomes important, Harbor and Higgins (2008) tentatively suggest adjectives of low for I^2 values between 25% and 50%, moderate for 50%-75% and high for values larger than 75% (in bold). ***,** and * denote significance at the 1%,5% and 10%, respectively.

How banks with different characteristics react to global uncertainty shocks

Table 7

	Size	Bank capital ratio	Bank liquidity ratio	Risk indicators	Revenue commercial BM	Revenue universal BM	Stable sources of funding	Volatile sources of funding	Profitability
Mean effect:									
MBR	0.0017	0.1452	0.005	-0.01	0.0024	-0.0004	0.0285	-0.0044	0.0017
CD	0.0051	**0.238****	0.0043	-0.0165	0.0128	**-0.0151***	**0.0423*****	-0.0017	0.1703
Percentage of heterogeneity (I^2):									
MBR	69.59	**81.85**	23.54	47.57	0.00	68.37	**78.97**	**85.98**	33.24
CD	47.29	**96.43**	13.13	**97.55**	0.00	**94.31**	61.39	0.00	55.85
Observations	5	5	5	5 (CD) 6 (MBR)	5	3(CD) 4 (MBR)	4 (CD) 5 (MBR)	3(CD) 4 (MBR)	4

Notes: MBR corresponds to the estimates with the multiple-banking relationships database and CD to the complete database, The mean effect 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 between-study variance. The I^2 statistic is 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. Although there can be no absolute rule for when heterogeneity becomes important, Harbor and Higgins (2008) tentatively suggest adjectives of low for I^2 values between 25% and 50%, moderate for 50%-75% and high for values larger than 75% (in bold). ***,** and * denote significance at the 1%,5% and 10%, respectively.

Appendix A: Meta-analysis techniques

Meta-analysis techniques are used when studies are not perfectly comparable, but evaluate the same or a closely related question. 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.

There are two approaches to meta-analysis: fixed and random effects models. A fixed effects approach is best under the presence of homogenous effect sizes, where the heterogeneity can be completely explained by the level of variation for each specific estimated coefficient (within-study sampling error). In a random effects meta-analysis two sources of heterogeneity are considered: within-study sampling error and the level of variability of estimated coefficients among the studies (between-study variance) (Card (2016)).

For the meta-analysis presented in this paper the random effects model is more suitable since there are important sources of heterogeneity between each study. Heterogeneity in the individual country studies arises from the institutional and regulatory frameworks of credit provision as well as from the individual country characteristics. 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 growth 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:

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

Based on this approach, we estimate two sources of variance: (i) within-study sampling error (σ_i^2) and (ii) the between-study variance (τ^2). The main result of this estimation corresponds to a range where the expected value of the effect of certain bank characteristics on credit growth could be located.

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

1- Estimate the level of heterogeneity among effect sizes (Q measure). The statistic is constructed using the squared weighted sum of the difference between the estimates and its average.
2- Calculate the magnitude of the level of heterogeneity in effect sizes (I^2 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 I^2 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 between-study variance.

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