DOCUMENT
DE TRAVAIL
N° 548

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AND THE CREDIT CHANNEL IN BRAZIL:
IDENTIFICATION AND EVIDENCE FROM PANEL DATA**

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Bank risks, monetary shocks and the credit channel in Brazil: identification and evidence from panel data ^{*†}

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^{*}I wish to thank Cameron McLoughlin, Ludovic Gauvin, Ramona Jimborean, Mathieu Gex, Sanvi Avouyi-Dovi, Filippo Ferroni, Anthony Dare, Meritzell Simón-Martín, Sebnem Kalemli-Ozcan, Andrew Powell and session participants at the 2013 Narodowy Bank Polski Workshop on Monetary Transmission, the 2014 Midwest Finance Association, Royal Economic Society, Inter-American Development Bank, and European Economic Association conferences for helpful comments. I am particularly grateful to Patrick Sevestre, Martin Missong, María Soledad Martínez-Pería, and Carlos Végh for insightful discussions on earlier versions of the paper. I am indebted to Brendan Vannier for outstanding research assistance. All remaining errors are my own responsibility. The opinions expressed here do not necessarily represent the views of the Banque de France or the Eurosystem.

[†]This paper has been published as: Ramos-Tallada, J., "Bank risks, monetary shocks and the credit channel in Brazil: identification and evidence from panel data", *Journal of International Money and Finance* (2015), doi:[10.1016/j.jimonfin.2015.02.014](https://doi.org/10.1016/j.jimonfin.2015.02.014).

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Abstract

Using a large database of bank financial statements, this paper investigates the determinants of the bank lending channel (BLC) of monetary transmission in Brazil between 1995 and 2012. I extend the standard empirical approach in two main ways. First, I apply a micro-founded strategy for disentangling demand from supply shifts in credit. Using this identification scheme, I show that lending supply is negatively correlated with the short-term market interest rate over the long period. The sensitivity of credit supply to monetary shocks is not related to the bank characteristics generally used in the empirical literature, whereas a proxy of the individual bank external finance premium (EFP) tends to capture financial constraints better than size, liquid assets or capitalization ratios. However, the patterns of the BLC have changed since the onset of the global financial crisis. In the post-crisis period, the money market rate does not affect the lending supply of the average bank anymore, while small banks and those lacking access to long-term funds appear more sensitive to monetary shocks in some estimations. Second, I check whether several types of uncertainty may drive the BLC, beyond liquidity risk. Over the long period, I find evidence that higher market risk borne by banks' securities portfolios (captured by a longer duration of public debt bonds) and lower uncertainty in the money market (captured by a lower volatility of rates) appear to consistently enhance the effectiveness of monetary policy through the BLC.

Keywords: Risks, Monetary policy transmission, Bank lending channel, Identification of supply shifts, Panel data, Brazil

JEL Classification: E44, E52, F4, G21

Résumé

Utilisant une large base de données sur les états financiers des banques, ce papier examine les déterminants du canal du crédit bancaire (CCB) dans la transmission de la politique monétaire au Brésil entre 1995 et 2012. J'élargis l'approche empirique standard de deux façons. Premièrement, j'utilise une stratégie micro-fondée pour différencier les déplacements de la demande de crédit de ceux de l'offre. Au moyen de ce schéma d'identification, je montre que, sur le long terme, l'offre de prêts est négativement corrélée avec le taux d'intérêt de court terme. La sensibilité de l'offre de crédit aux chocs monétaires n'est pas liée aux caractéristiques des établissements bancaires généralement utilisées dans la littérature empirique. Ainsi un proxy de la prime de financement externe des banques tend à mieux capter les contraintes financières que la taille, les ratios de liquidité ou de capital. Néanmoins, le mode de transmission via le CCB a changé depuis l'éclatement de la crise financière globale. Suite à cette dernière, le taux du marché monétaire n'affecte plus l'offre de prêts de la banque moyenne, alors que les banques de petite taille et celles ayant un accès restreint aux ressources de long terme apparaissent plus sensibles aux chocs monétaires dans certaines estimations. Deuxièmement, je teste si divers types d'incertitude autres que le risque de liquidité ont une influence sur le CCB. Empiriquement, sur le long terme, plus le risque de marché dans le portefeuille de titres des banques (capté par une duration plus longue des obligations d'état) est élevé et plus l'incertitude sur le marché monétaire (captée par la volatilité des taux courts) est faible, plus la transmission de la politique monétaire via le CCB apparaît comme efficace.

Mots clé: Risques, Transmission de la politique monétaire, Canal du crédit bancaire, Identification des déplacements de l'offre, Données de panel, Brésil

Codes JEL: E44, E52, F4, G21

Non-technical summary

The bank lending channel (BLC) is a mechanism through which monetary policy shocks are transmitted to the real sector via shifts in the banks' lending supply. The higher the sensitivity of banks' credit supply the more active the BLC is, and the more effective monetary policy tends to be. As it is well established that the real sphere is affected to some extent by credit availability, the BLC is crucial to policy-making: if it is not active, central banks may lack an important tool to stabilize inflation; but if the lending supply is too sensitive, the BLC might give rise to a sudden process of overheating or a sudden stop of economic activity -increasing the volatility of output.

In Brazil, the authorities' interest in the effectiveness of monetary policy transmission via the BLC has but increased. The ratio of bank credit over GDP has risen from barely 25% in 2003 to around 55% in 2013, so that its impact on real activity is likely to have strengthened significantly. Yet, to what extent the supply of credit is sensitive to a change in the banks' perception of monetary policy stance (i.e. to a monetary shock)? And what are the main drivers of the BLC? This article investigates both questions using panel data from the financial statements of banks operating in Brazil between 1995 and 2012 and testing diverse measures of monetary policy stance, such as observed, expected, or independent from policy-reaction money market rates.

In the usual empirical literature, the credit response to a change in monetary policy is implicitly based on the bank's optimization of liquidity risk. The lending supply is likely to be more sensitive to a monetary shock for banks facing a higher external finance premium (EFP) and a tighter liquidity constraint. Although these variables are difficult to observe, the empirical studies use some proxies based on banks' financial structure. For example, banks' size, liquid assets, capitalization ratios, and foreign or public ownership are assumed to loosen liquidity constraints, thus to attenuate the BLC. Moreover, finding significant heterogeneity in the responses across banks' categories is considered as evidence of credit supply shifts -thus of an active BLC.

Yet, the results on the factors driving the BLC are often inconclusive. Among others, the empirical literature faces two challenging issues. (i) Disentangling lending supply from credit demand shifts is a difficult task. On the one hand, disaggregated data on loan requests from bank lending surveys are often confidential. On the other hand, using bank-specific variables does not completely solve the identification issues: for example, finding that domestic banks' credit is relatively more responsive to monetary shocks may not necessarily imply a more sensitive supply, but a more resilient demand for credit faced by foreign banks. For the latter may be driven by global rather than local monetary conditions. (ii) The usual empirical specification of risks faced by banks when responding to a monetary shock is likely to be incomplete. The latter relates to the inability to take into account the role played by unobservable factors, such as expectations or risk premiums. This paper seeks to address these two issues.

The first contribution of this work is the use of a micro-founded strategy based on publicly available data to disentangle lending responses driven by bank supply from movements attributable to the demand for loans. I compute a proxy for the lending interest rates and use it jointly with the variations in outstanding credit to identify periods in which credit growth was driven by supply at the individual bank level. This method makes it possible to estimate the importance and the drivers of the BLC using only supply-driven observations, as well as comparing results with demand-driven regressions of credit growth. Several tests corroborate the validity of the identification method.

Using this strategy, I show that the lending supply of the average bank is negatively correlated with the short-term market interest rate (called *Selic* in Brazil) over the whole sample interval (1995-2012). In turn, bank financial and ownership structures don't appear to have constrained the bank responses to monetary shocks over the long period. In fact, a computed proxy for bank-specific EFP captures financial constraints better than size, liquidity or capitalization ratios. When moving from the whole sample period to the post-crisis era (from 2007 Q3 onwards), the analysis suggests a change in the BLC patterns, with potentially relevant policy implications for Brazil: monetary policy might be no longer transmitted via the average bank lending, but through small banks and those lacking access to long-term funds -the financial constraints of which are likely to be binding since the onset of the global financial crisis.

As a second contribution to the empirical literature, I extend the analysis of the BLC drivers to variables capturing different types of uncertainty beyond liquidity risk. In the case of Brazil, I find evidence that the lending supply is more sensitive to monetary shocks when banks face higher ex-ante systematic market risk (captured by the duration of marketable public securities) and a lower volatility of market rates. The intuition behind this result is as follows: *ceteris paribus*, the standard approach considers two banks holding the same liquidity ratio as equally sensitive to monetary policy -since all liquid assets are implicitly considered equivalent to cash. Yet, this is unlikely to occur in practice: the liquidity ratio includes some marketable securities with a longer maturity or duration than money market instruments, so that their price is negatively affected by increases in short-term rates. As monetary policy tightens and deposit withdrawals need to be balanced on the bank's asset side, the realization of market risk may make it costly for "liquid" banks to sell securities. Therefore, they may be willing to reduce their credit portfolio rather than to fully insulate it from the shock. Moreover, high uncertainty implied by volatility undermines the ability of banks to forecast potential gains/losses, smoothing their response to monetary shocks.

Some policy implications can be drawn from the latter results: providing a context for more stable and easily predictable money market rates and lengthening the maturities of public debt could help unclog an important transmission mechanism of monetary policy.

1 Introduction

The latest IMF Article IV report on Brazil ([IMF, 2013](#)) devotes a whole chapter to investigating whether the effectiveness of monetary policy through the credit channel has weakened in recent years. The question is of special interest: in a country where the ratio of bank credit over GDP has risen from barely 25% in 2003 to around 55% in 2013, the impact of bank lending supply on real activity is likely to have strengthened significantly.

The narrow credit channel, called also bank lending channel (BLC), is a mechanism through which monetary policy shocks are transmitted to the real sector via shifts in the banks' lending supply.¹ The extent to which the lending supply responds to a monetary shock determines whether a BLC exists and is active in a given economy. The higher the sensitivity of banks' credit supply, the more effective monetary policy is. The BLC is therefore key to policy-making: if it is not active, central banks may lack an important tool to stabilize inflation; but if the lending supply is too sensitive, the BLC might give rise to a sudden process of overheating or a sudden stop of economic activity, increasing the volatility of output.

The establishment of the theoretical foundations of the BLC by [Bernanke & Blinder \(1988\)](#) has led to the emergence of a wide range of studies in this area. [Romer et al. \(1990\)](#), [Kashyap & Stein \(1993, 1997\)](#), [Friedman et al. \(1993\)](#), [Ramey \(1993\)](#), [Bernanke & Gertler \(1995\)](#), [Trautwein \(2000\)](#) and [Walsh \(2003\)](#), amongst others, have dealt with theoretical and policy aspects. In addition to its importance for policy-making, the BLC has prompted a lively debate because its economic foundations remain controversial, and empirical evidence on the determinants is not clear-cut. First, econometric studies, particularly those using aggregate data, face a challenging identification problem: when a monetary shock occurs, it is difficult to determine whether variations in the observed outstanding credit are driven by the demand for or by the supply of loans (see for example [Peek & Rosengren, 2013](#)). Second, the transmission of monetary policy is driven by variables that may either be imperfectly measured, such as risk premiums, or unobservable, such as expectations ([Issing, 2003](#)).

To overcome the identification problem, numerous empirical studies use a panel-based micro-econometric approach, applied either on static models ([Kashyap & Stein, 1995](#); [Favero et al., 1999](#); [Arena et al., 2006](#); [Olivero et al., 2011a,b](#)) or on dynamic specifications ([Kashyap & Stein, 2000](#); [Kishan & Opiela, 2000](#); [Ehrmann et al., 2003](#); [Gambacorta, 2003](#); [De Haan, 2008](#); [Kishan & Opiela, 2006](#); [Ashcraft, 2006](#); [Pruteanu-Podpiera, 2007](#); [Altunbas et al., 2010](#); [Gambacorta & Marques-Ibanez, 2011](#); [Wu et al., 2011](#); [Kandrac, 2012](#); [Bluedorn et al., 2013](#)).² The main explanatory variable, a monetary shock, is generally

¹In the context of the BLC, the term "monetary shock" refers to a shift in the supply of the money base involving a change either in the bank deposit base or in the money market rate.

²See also the special issue of the Journal of Banking and Finance (2002, n.26) and [Angeloni et al. \(2003\)](#) (part 3), which collect many other empirical works.

measured as a change in the observed money market rates.³ The usual specification is founded on the main hypothesis underlying the BLC: market imperfections faced when collecting funds and the related external finance premium (EFP) differ across banks. Implicitly, the credit response to a monetary shock is based on the bank's optimization of a liquidity risk. The lending supply is likely to be more sensitive to a monetary shock for banks facing a higher EFP and a tighter liquidity constraint. Although these variables are difficult to observe, standard empirical literature uses some proxies based on banks' financial structure: for example banks' size, liquid assets, capitalization ratios, and foreign or public ownership are assumed to loosen liquidity constraints, thus to attenuate the BLC.

The use of bank-specific variables is intended to solve identification issues, since a significant heterogeneity across banks' responses is assumed to signal credit supply shifts. Properly taking into account credit demand is in turn a challenging task. The empirical studies generally use macroeconomic variables, such as GDP growth and inflation. Indeed, when surveys on aggregate loan demand are publicly available, as in Brazil, the span of the data may not be deep enough. Some recent works use detailed disaggregated data on bank lending surveys, but this information is often confidential (e.g. [Hempell & Sørensen, 2010](#)). Among other factors, this failure to capture the heterogeneity of the demand for credit faced by banks may lead to inconclusive results. The estimated role of bank-specific characteristics is not unequivocal. In some cases, some of the variables expected to dampen the BLC may instead appear to amplify it, such as bank size (see the references below on Brazil) or liquidity ratios ([Gambacorta & Marques-Ibanez, 2011](#); [Olivero et al., 2011b](#)). Moreover, the extent to which bank credit responds to a monetary shock tends to vary significantly across countries and over time.

Brazil is an illustration of this puzzle. Credit and economic activity seemed to be quite insensitive to sharp increases in money market rates in the late 1990s and the early 2000s. As a consequence, one of the main concerns of the Banco Central do Brasil (BCB -Central Bank of Brazil) has traditionally centered on "monetary policy ineffectiveness, presumably derived from blockages in the transmission mechanism (low credit-to-GDP ratios and limited if not perverse wealth effect owing to a large share of floating rate public debt)" ([Bevilaqua et al., 2008](#), p. 6). More recently, a relatively moderate monetary tightening in 2010 and 2011 had deep and permanent effects on the real economy. However, anecdotal evidence suggests that credit might have been quite insensitive to monetary stimulus in the easing cycle that followed in 2012 (see [García-Escribano, 2013](#)).

It is well established that real activity is affected to some extent by credit availability. Yet, when observed bank credit responds to a monetary shock, how can lending supply shifts be disentangled from demand movements? And what factors drive the sensitivity of lending supply to monetary policy? Based on

³Money market rates do reflect the current supply conditions in the market for bank reserves as long as they are explicitly or implicitly targeted by monetary authorities (see [Bernanke & Mihov, 1998](#)).

an initial sample of almost one hundred banks between December 1995 and September 2012, this paper investigates these two questions for the case of Brazil. Seeking to address some of the key issues raised in the above literature, I extend the standard approach as follows.

The first contribution of this work is the use of a micro-founded strategy based on publicly available data to disentangle lending responses driven by bank supply from movements attributable to the demand for loans. Econometric checks based on the distinct impact of the coefficient of reserves requirements, aggregate outcome, and loan requests on each of the series corroborate the reliability of the identifying method I put forward. Using this strategy, I provide consistent evidence that lending supply is negatively correlated with the short-term market interest rate (called Selic in Brazil) over the long period. However, the response to monetary shocks is not related to the bank characteristics generally used in the standard literature. I find that a proxy of the individual bank EFP captures financial constraints better than size, liquidity or capitalization ratios. Moreover, while credit supply of foreign banks does not react differently from that of their peers, in most of the estimations I find that their credit demand is relatively more resilient to domestic monetary shocks. This pattern illustrates the risk of misguided conclusions when failing to identify the heterogeneity of demand faced by banks, as the attenuating role in the BLC of foreign subsidiaries could be attributed to their access to funds from the parent company. While the latter is a well-established fact, it does not necessarily imply that the resilience of foreign banks' observed credit is due to supply. Global banks' customers often have internationally oriented activities. Therefore, their credit demand may be driven by global rather than local monetary conditions (see [Cetorelli & Goldberg, 2012](#)).

I also find evidence that the patterns of the BLC have changed since the onset of the global financial crisis. From 2007 Q3 onwards, the money market rate no longer appears to have affected the lending supply of the average bank, while small banks and those lacking access to long-term funds sometimes appear more sensitive to monetary shocks. The effect of size and long term borrowing is not robust to all estimations, though. In general, common factors related to risks other than illiquidity remain the main drivers of the BLC in Brazil.

The latter result constitutes the second contribution of this paper to the empirical literature. I extend the analysis of the BLC drivers to variables capturing different types of uncertainty beyond liquidity risk. In the case of Brazil, I generally find that the higher the ex ante systematic market risk (captured by the duration of outstanding marketable public securities) and the lower the volatility of market rates, the stronger the bank lending response to monetary shocks is. The intuition behind this result is as follows: *ceteris paribus*, the standard approach considers two banks holding the same liquidity ratio as equally sensitive to monetary policy, since all liquid assets are implicitly considered equivalent to cash. Yet, this is unlikely to occur in practice: the liquidity ratio includes some marketable securities with a longer maturity

or duration than money market instruments, so that their price is negatively affected by increases in short-term rates. As monetary policy tightens and deposit withdrawals need to be balanced on the bank's asset side, the realization of market risk may make it costly for "liquid" banks to sell securities. Therefore they may be willing to reduce their credit portfolio rather than to fully insulate it from the shock. Moreover, high uncertainty implied by volatility undermines the ability of banks to forecast potential gains/losses, smoothing their response to monetary shocks.

These findings are generally robust to the use of alternative samples of banks and measures of the stance of monetary policy. Among others, I find evidence that (to a lesser extent than observed shocks) changes in expected short-term rates significantly affect lending supply, which suggests a forward-looking behaviour on the part of banks.

Along with the above literature, this paper is related to other empirical studies using panel data to investigate the BLC in Brazil. The time span and methodologies differ across them, but in general the more the sample period of estimation is recent, the more active the BLC tends to be. The post-crisis period is in general not covered, though. Over the 1994-2001 period, only reserve requirements appear to discourage bank lending. The latter is found to be insensitive to the short-term rate ([Takeda et al., 2005](#)) or even positively related to it ([Graminho & Bonomo, 2002](#)), which suggests that liquidity constraints were not binding at the time. Later studies covering up to the mid-2000s find evidence that bank lending has become sensitive, either to the impact of the Selic rate on liquidity constraints ([de Oliveira & Neto, 2008](#)) or else to market surprises relative to the expected target ([Coelho et al., 2010](#)). The latter paper proposes an interesting approach for identifying lending supply shifts, using daily bank-level data and an event study approach based on the minutes of the Monetary Policy Committee (Copom). Yet, such a data-intensive approach raises some challenging issues: suitable control regressors have much less frequency than the dependent variables in the panel, and the sample period (2001-2006) is shortened by the availability of data on bank-level effective lending rates. Interestingly, the above studies tend to find that large banks' lending is either insensitive or even more responsive to changes in the monetary policy stance. They also provide anecdotal evidence on the ability of small and medium-sized banks in Brazil to substitute deposits for other sources of funds. Still, this common finding refers to the pre-crisis era. In turn, using aggregate data on loan requests to control for demand (Serasa indexes), [García-Escribano \(2013\)](#) finds evidence that the BLC was active over 2005-2012. She cannot conclude that the BLC was dampened by domestic factors during the 2012 easing monetary cycle, in spite of anecdotal evidence. Instead, external macro-financial factors, such as the rise in sovereign risk, weakened the effectiveness of monetary policy in 2012. Again, the scope of the analysis is somehow constrained by the span of the survey on loan requests, the data for which are available only from 2007 onwards. In contrast with the latter studies, the identification strategy that I

propose uses data on bank financial statements to proxy the bank-level implicit lending rates (see below).⁴ The early availability of these data makes it possible to carry out the empirical analysis over a longer span than any of the papers above, while disentangling in a reliable way credit demand from supply. In line with the empirical literature on the BLC in Brazil, I do not find consistent evidence that bank financial and ownership structures have constrained the bank responses to monetary shocks over the long period. Yet, the analysis of the post-crisis era yields new conclusions: small size and a lack of access to long-term funds might have become amplifying factors of the BLC, suggesting that some financial constraints are likely to be binding for banks in Brazil.

This paper is structured as follows: section 2 presents the two micro-founded frameworks used for the empirical estimation; section 3 describes the data and the empirical methodology, including the identification strategy of lending supply shifts; section 4 presents the main results of estimations, including a number of robustness tests; section 5 concludes.

2 Bank risks and the lending channel: literature review

2.1 The standard precautionary approach

Traditionally, in the standard literature on the BLC, the specification of the empirical response functions and the interpretation of the results are based on micro-foundations related to a precautionary behaviour of banks. The latter was formalized by Kashyap & Stein (1995), Stein (1998) and Kishan & Opiela (2000). Within this framework, items of bank balance sheets are imperfectly substitutable owing to market frictions. In terms of assets, the high content of private information makes loans illiquid, as opposed to marketable securities. As for liabilities, insured deposits are subject to "taxes" (compulsory reserves, contribution to deposit insurance), while the issuance of uninsured liabilities such as certificates of deposits (CDs) gives rise to agency costs. Banks therefore have to pay an extra cost for their CDs over the riskless interest rate, referred to as "external financial premium" (EFP). Yet, the type of imperfections put forward by the precautionary approach results mainly in a liquidity risk, caused by the transformation of deposits into credit. Implicitly, the standard approach is based on a financial repression hypothesis. Faced with a monetary tightening, banks cannot counter a reduction in their deposit base by raising deposit rates. The deposit base is thus exogenous and uncertain, and the monetary tightening translates into liquidity risk. Therefore, the inability of banks to overcome this risk -either by holding securities ex ante or by issuing CDs-, determines the extent of their response to a shock and the importance of the BLC in

⁴I use the Serasa index on loan requests to validate the identification scheme since 2007, but not as a control in the BLC regressions.

the economy.⁵ When a monetary tightening leads to a reduction in the deposit base, the fewer liquid assets (securities) a bank holds and the more costly is the replacement of CDs for the bank's deposits, the more the bank is forced to reduce its credit supply. In this approach, the financial structure (composition of the balance sheet, size and ownership of financial institutions) plays a key role in determining the importance of the BLC. Some factors are likely to ease the liquidity constraint of banks and to dampen the efficiency of transmission (see variables 1 and 2 below). Other individual characteristics tend, in turn, to loosen the market discipline exerted by uninsured depositors, which also mitigates the importance of the BLC (see variables 3, 4, and 5 below). In all, the precautionary approach establishes that the following factors are likely to attenuate (enhance) the sensitivity of lending supply to monetary shocks.

- (1) A high (low) ratio of liquid assets;
- (2) A majority foreign ownership that gives access to external liquidity sources;⁶
- (3) A low (high) EFP;
- (4) A large (small) size of financial institutions;⁷
- (5) A majority public ownership that involves explicit or implicit insurance.⁸

2.2 A diversification approach

[Santomero \(1997\)](#), [Barnhill et al. \(2002\)](#) and [DeYoung et al. \(2005\)](#) have highlighted the rationale for banks to jointly manage their major balance sheet risks when it comes to deciding on the volume and the composition of their credit portfolio. The idea that a mere additive approach to risks can lead to a misspecification of the overall balance sheet exposure has been raised by studies on the regulation of banking capital (see [Alessandri & Drehmann, 2009](#)). Moreover, the role of the diversity and the interdependency of risks has influenced the literature on the BLC. Recent applied studies highlight a "risk taking channel", following the processes of deregulation and financial innovation (see [ECB, 2008](#); [Borio & Zhu, 2012](#)). According to the risk taking channel, prolonged periods of low interest rates are likely to lead banks, particularly well capitalized ones, to increase their risk-tolerance, which changes the drivers of the transmission of monetary policy ([De Nicoló et al., 2010](#); [Altunbas et al., 2012](#)). Other authors have also stressed alternative mechanisms to liquidity risks in the transmission of monetary policy. [Chmielewski \(2005\)](#) suggests that banks' preference for risk and the impact of short-term rate variations on the distribution of default risks play a role in the narrow channel. In the context of the "banking

⁵Unless otherwise specified, with a view to shortening the expression, the term "response to shocks" refers to banks' willingness to modify their credit supply in response to a monetary shock. In general, studies on the BLC focus on the contractionary effects of monetary policies on the real sphere. Therefore, in this paper the discussion will develop in terms of monetary tightening.

⁶See [De Bondt \(1999\)](#), [Arena et al. \(2006\)](#) and [Cetorelli & Goldberg \(2012\)](#) for a discussion about the capacity of foreign and global banks to isolate their outstanding volume of credit from monetary shocks.

⁷For instance, [Berger et al. \(1995, p. 29\)](#) report that "Empirical studies usually found that bank risk affects uninsured deposit rates, but the effect was typically weaker for banks that may be 'too big to fail'".

⁸[Ehrmann et al. \(2001, p. 10\)](#) highlight the guarantees offered by the state to depositors in public banks.

capital channel", [Van den Heuvel \(2006\)](#) draws attention to the role of interest rate risk. Owing to the maturity transformation characteristic of balance sheets, the perspective that a rise in short-term rates erodes the value of own funds may encourage banks to reduce their credit supply, as the latter option is less costly than issuing new capital to comply with regulation. In turn, interest rate risk can be mitigated when banks hold large portfolios of low duration securities. In this case short-term interest rate rises do not entail potential losses, as documented by [Graminho & Bonomo \(2002\)](#) in the case of Brazil. [Altunbas et al. \(2010\)](#) posit that, along with standard bank characteristics, the way depositors perceive credit risk on the asset side of the bank balance-sheet plays a significant role in monetary policy transmission. For the pre-global crisis period in the euro area, they find that high-risk banks were less able to insulate their lending from monetary shocks as they had worse prospects and less access to uninsured fund raising than low-risk banks. Still, in their broad survey [Borio & Zhu \(2012\)](#) acknowledge that relatively little attention has been paid in the literature regarding monetary transmission to banks' perception of and attitude towards risks.

The idea that the BLC can be driven by factors other than liquidity constraints therefore underpins some recent works. Although they do not follow a common research line, I use the term *diversification* to refer to this logic of monetary policy transmission. The diversification approach is based on an active joint management of diverse banking risks and is complementary to the standard precautionary approach. The above discussion provides a rationale for investigating the role in the BLC of alternative sources of uncertainty. The intuition is as follows. On the one hand, the factors that urge banks to actively manage balance-sheet risks in the event of shocks (due to potential gains/losses or market discipline) increase their willingness to alter their credit supply (see variables 1, 2, and 3 below). On the other hand, the variables that discourage ex ante banks to adopt a risky balance sheet structure tend to reduce the significance of the BLC (see variable 4 below). In all, the following factors are likely to mitigate (enhance) the sensitivity of the lending supply to monetary shocks.

- (1) A loose (strong) market discipline exerted by uninsured depositors via the EFP;
- (2) Short (long)-term maturities of the securities held in portfolio;
- (3) A high (low) degree of uncertainty perceived by banks on credit losses;
- (4) A high (low) volatility of short-term interest rates;

Applied to the Brazilian context, this work tests the main predictions of the precautionary and diversification approaches to the BLC.

3 Data and empirical methodology

3.1 Data description and variables construction

The dataset was built from files made available by BCB (www.bcb.gov.br). It encompasses the main bank balance sheets and income statements of the 98 largest banking groups carrying out some commercial activity and operating in Brazil up to September 2012. The sample period (T) ranges from December 1995 to September 2012. These statements were published twice a year until December 1999 and quarterly thereafter. Along with individual banking data, series on the macrofinancial variables (money market interest rates, coefficients of compulsory reserves, duration of public bonds) were also collected from the BCB. Details on sources and the construction of variables can be found in Table 1.

In constructing the initial panel, changes in bank ownership or control (restructuring, privatizations, merger and acquisitions) were addressed through backwards integration. The acquirer bank and the acquired bank are considered the same entity, so that their accounting statements are consolidated throughout the whole sample period.⁹

The variables featuring the bank's balance-sheet structure have been defined in order to test the micro-foundations of the lending channel. For the dependent variable (loans growth), I chose a broad aggregate of gross credit (not net of provisions). Along with loans in reais (local currency), it includes some types of financing to export indexed to foreign currency, which are actively used by Brazilian banks (see Appendix). As regards the main explanatory variable, my baseline empirical model uses the observed money market rate (Selic), which is the measure of a monetary shock broadly used in the empirical literature on the BLC. In an alternative specification, I also investigate the role of expected money market rates. As a measure of the latter, I use the consensus forecast survey conducted by the BCB from November 2001 onwards, and simulations from a rolling-window estimated ARIMA model when data on market forecasts were not available (1995-2001).¹⁰ Lastly, for robustness checks I estimated a VAR model-based measure of the monetary policy stance in Brazil, using standard macroeconomic variables (see below).

In turn, two types of factor affect the sensitivity of the lending response to a given monetary shock.

The precautionary factors are captured by the variables traditionally used in the standard BLC empirical literature. Related to bank-specific characteristics, they intend to capture some heterogeneity in the liquidity constraint faced by banks. As disclosed in Table 1, I computed ratios of liquid assets, capitalization and long term borrowing relative to the average of the whole sample of banks over the sample period, so

⁹This method is used among others by [Peek & Rosengren \(1995\)](#), [Ehrmann et al. \(2003\)](#) and [Kishan & Opiela \(2006\)](#). Table B.1 in Appendix B provides detailed information on the evolution of the banking industry in Brazil in terms of changes in ownership for the banking groups that compose the initial panel.

¹⁰The estimation of the proxy for interest rate expectations can be found in Appendix A

Table 1: Data sources and definition of variables

		(1)	Variable	Definition		Source/computation	
Dependent variable		i	Loans growth	% growth of outstanding total gross loans (L_{it})		BCB/SFN ⁽²⁾ (see Appendix) $100 \cdot \Delta \log(L_{it})$	
Monetary shock		c	ΔR	Variation (1 st diff.) of observed money market rate (SELIC)		BCB /Séries temporais (n.4189)	
		c	ΔER	Variation (1 st diff.) of expected market rate		ARIMA forecast (1995Q4 - 2001Q4) BCB /Séries temporais /Expectativas do mercado (2001Q4 - 2012 Q4)	
		c	ΔMP	VAR-model based measure of a shock on the SELIC rate		Residuals (1 st diff.) from the interest rate equation of a 2-lag, 6 variables VAR model using data from BCB (see Section 4.3)	
Factors affecting the sensitivity of lending response to a monetary shock	Precautionary factors	i	Liquidity ratio	Relative ratio of :	Liq_{it} = Interfinancial assets + bonds	BCB/SFN	$\frac{X_{it}}{S_{it}} - \frac{1}{T} \sum_t \left(\frac{1}{N_t} \sum_i \frac{X_{it}}{S_{it}} \right)$
		i	Capital ratio		K_{it} = own funds		
		i	LT borrowing ratio		LTB_{it} = long-term borrowing		
		i	Size ratio		S_{it} = total assets		
		i	Foreign ownership	Foreign bank or under the control of a foreign bank at time t			Dummy = 1 if true; 0 otherwise
		i	Public ownership	State or federal bank at time t			Dummy = 1 if true; 0 otherwise
		i	ΔEFP	Variation (1 st diff.) of external finance premium (EFP_{it})			Proxy for RN then $EFP_{it} = RN_{it} - R_t$
	Diversification factors	i	NPL Ratio ⁽³⁾	Ratio of non-performing loans (NPL_{it}) over total loans			$100 \cdot \frac{NPL_{it}}{L_{it}}$
		c	Duration growth	% growth of the duration (m_t) of outstanding marketable public debt		BCB /Séries temporais (n.10620) $100 \cdot \Delta \log(m_t)$	
		c	Volatility	Moving standard deviation of the daily SELIC rate over last semester/quarter		Computed from BCB /Séries temporais (n.1178)	
Identification of lending supply shifts		i	DemandL ⁽⁴⁾	$DL_{it} = \Delta Loans_{it} \cdot \Delta RL_{it}$		Proxy for RL then Dummy = 1 if $DL_{it} > 0$; 0 otherwise	
Control variables		c	RRT	Coefficient of required reserves on time deposits		Datastream	
		c	GDP	Seasonally adjusted GDP growth over the last semester/quarter		Computed from BCB /Séries temporais (n.1253)	
		c	INF	Variation of general price index (IGP-M) over the last semester/quarter		Computed from BCB /Séries temporais (n.189)	

Notes :

¹ c/i stand respectively for "common to all banks" / "bank-specific variable"² BCB / Sistema financeiro Nacional / Informações cadastrais e contábeis³ The NPL Ratio is also used as a control variable (thus without interacting it with ΔR or ΔER)⁴ DemandL is not included in the regression but used to drop demand-driven observations (see below)

that the sum of any of these variables over T is zero.¹¹

In turn, the ratio of size is relative to the average of the whole sample of banks for each period t . Since changes in the latter variable over time depend on both the size of the bank i and the size of the banking sector, any trend due to growth in the nominal value of assets is expunged.¹² Other bank individual characteristics such as public or foreign ownership are defined as dummy variables that can vary over time for a given bank.

In order to capture the degree of market discipline exerted by depositors, I computed a proxy of the average deposit rate (RN) as the ratio of interest expenses paid by each bank at t over the addition of its insured deposits plus uninsured short-term funds outstanding at $t - 1$.¹³ Then the individual external finance premium (EFP) is proxied by subtracting the prevailing money market rate (R) from RN . As the average banks' cost of deposits and short-term funds closely tracks the money market rate, the cross-section mean of EFP fluctuates around zero except in 2008, when it rockets due to the extreme uncertainty surrounding the failure of Lehman Brothers (see Figure 3).

The *diversification* factors seek to capture non-liquidity risks. Drawn from the individual balance sheets, the percentage of non-performing loans ($NPL\ Ratio$) proxies the ex ante credit risk perceived by each bank. In turn, *Volatility* and the *Duration growth* of bonds vary only over time, not across banks. The former gives a measure of ex ante uncertainty in the money market, whereas the latter captures the sensitivity of the bank portfolio of marketable securities to a change in short-term interest rates.

In line with the empirical literature, the seasonally adjusted quarterly rates of inflation and GDP growth are used as control variables. Along with them, I included the coefficient of required reserves on term deposits (RRT , which in Brazil represent a larger amount than other types of insured liabilities such as sight or savings deposits), and the ratio of non-performing loans drawn from individual bank statements.

In order to identify shifts in the supply of loans, I built a proxy for the lending rate (RL) in the same way as for the implicit deposit rate: for each bank, RL is computed as the ratio of its interest revenues from loans in the last semester/quarter over the amount of total outstanding gross credit during the previous period. Then I define DL_{it} as the product of ΔRL and the observed growth of loans. I assume that, at the equilibrium of the credit market, changes in lending are driven rather by demand if they imply a variation of same sign of RL (see Figure 1). Then, for a given bank and period, $DemandL$ is a dummy variable that takes zero values if the sign of DL_{it} is negative (i.e. if supply dominates over demand), and is equal to

¹¹Along with liquidity, size and capitalization, commonly used in the literature, I added the item "long-term borrowing" (*obrigações por empréstimos e repasses*). In Brazil, the latter balance-sheet item often includes subsidized resources transferred to banks by the public sector (*repasses*). Banks with access to those funds are likely to be less liquidity-constrained when responding to a monetary shock.

¹²This way of constructing variables related to bank individual characteristics is common in the literature on BLC. See e.g. Ehrmann et al. (2003) and Kishan & Opiela (2006).

¹³Arena et al. (2006) and Martínez Pería & Schmukler (2001) compute a similar proxy to capture the market discipline exerted by the depositors.

one otherwise. Note that $DemandL$ is not included in the regression (which would entail an endogeneity bias) but used as a selection device to disentangle supply-driven shifts of credit from demand-driven ones (see below).

Some banks were not operating either at the beginning or at the end of the sample period. In order to avoid selection bias I did not remove any bank or period from the original database before dealing with outliers. Therefore, the panel is unbalanced. This can affect unit root tests and render some types of specifications, such as individual random effects, questionable. However, OLS estimations remain reliable, once the heteroskedasticity of errors is taken into account (see [Sevestre, 2002](#)). With the exception of volatility and the NPL ratio, the regressors were specified either in first differences or in growth rates. For the whole sample period, all variables included in the regressions proved to be stationary at the usual significance levels.¹⁴

Figure 1: Demand and supply-driven shifts in the credit market

The initial sample of ninety-eight depository institutions (called "Consolidado I" in the BCB database) accounted for about 85% of the financial system assets as of September 2012. The remaining volume corresponds essentially to development banks, such as BNDES, that are excluded from the analysis. I deal with this database following two criteria commonly used in empirical studies on large panels of banks.

¹⁴The NPL ratio being a bank-specific variable, no common unit root process could be found through the [Levin et al. \(2002\)](#) test. The existence of individual unit root processes was in turn rejected by the [Im et al. \(2003\)](#) test. The latter test rejected also the hypothesis of non-stationarity for the variable *Volatility*, which is computed as a moving average throughout the last semester/quarter so that its trend is somehow expunged.

A first filter in levels seeks to discard from the analysis financial institutions for which intermediation credit-deposits remains a minor activity. I removed banks fulfilling at least one of the following conditions on average over the total observation period (Dec.1995 - Sep.2012): (i) the addition of insured deposits and short-term uninsured liabilities (funds collected on the open market, interfinancial deposits and CDs issues) represented less than 10% of total liabilities; (ii) total loans represented less than 20% of total assets. Eight small banks were dropped from the panel following these criteria, which left a "large" sample of ninety banks accounting for 86% of total outstanding credit in the financial system.¹⁵

Then a second filter in variations was applied to remove outliers. Twenty-one banks for which the credit growth rate exceeded in absolute value the average growth in the sample plus three times the standard deviation at least at two "interior" dates were dropped.¹⁶¹⁷ This filter seeks mainly to rule out abnormal rises in outstanding loans stemming from a merge-acquisition instead of from bank behaviour, which might bias the analysis of lending supply. Thereby, a number of foreign banks that had entered the Brazilian market in the second half of the 1990s were dropped from the large sample.

Last, as in [Takeda et al. \(2005\)](#), I removed Caixa Econômica Federal (CEF), a big public bank that benefits from subsidized funds and holds a huge share of housing credit in the Brazilian market. A sizeable part of that portfolio was transferred to the Public Treasury in 2001, which could distort the analysis.

This leaves a final "restricted" panel composed of 68 individuals, representing 81% of credit of the large sample.¹⁸ Figure 2 depicts the variation in the aggregate banking sector size and balance sheet structure throughout the period of analysis. Figure 3 shows how the sample average of the main bank-specific variables changed over time.

¹⁵The discarded bank codes were BNAC, BEXS, JOHN, KDB, LAPR, LARE, NATX, WESU.

¹⁶To avoid dropping too many individuals from the panel, banks with only one "interior" outlier, other than at the first or the last date, were kept in the sample. In the latter case, only the observations were removed (ie. the "interior" outlier and the "extreme" one if any).

¹⁷The discarded banks' codes were BANI, BARC, BBM, BCGB, BNP, BOC, BRAS, PACT, BTMU, CAGR, CSUI, DEUT, FATR, ING, JPMC, KEB, MODA, RABO, RAND, SOCO, VR.

¹⁸[Favero et al. \(1999\)](#), [Arenas et al. \(2006\)](#) and [Olivero et al. \(2011a,b\)](#) carry out a similar treatment of outliers to prevent estimations from reflecting institutional changes rather than bank lending behaviour.

Figure 2: Evolution of the aggregate banking sector (68 banks sample)

Source : author's calculations from BCB data

Figure 3: Evolution of sample averages of bank-specific variables

Source : author's calculations from BCB data

3.2 Empirical methodology

The empirical specification used here assumes that banks' decisions on their balance sheet structure at t are mainly based on the value taken by explanatory variables during the last period. In turn, the dependent variable reflects the outcome of the banks' choice on their planning horizon. The response function is defined as the rate of variation of outstanding credit of bank i between t and $t + j$ ($\Delta \log L_{i,t+j}$) triggered by a monetary shock occurring between $t - j$ and t ($R_{s,t}$ in the baseline model). I use alternative measures of a monetary shock, all of which are based on the money market rate at time t : the observed rate R (as baseline), the expected rate ER , and a VAR model-based measure MP (for robustness checks).

All the explanatory variables are therefore introduced with one lag, which helps to prevent endogeneity biases.¹⁹ Since the length of the interval of observation is quite large and varies during the period of analysis (a semester from December 1995 to December 1999, then a quarter from March 2000 onwards), I chose not to introduce further lags of the regressors in the BLC estimations.

In order to check the existence and the drivers of the BLC I use a dynamic model with compounded-coefficients, as specified in equation (1):

$$\Delta \log L_{i,t+j} = C + \beta_l \Delta \log L_{i,t} + \beta_s R_{s,t} + \sum_{k=1}^K \beta_k (R_{s,t} X_{k,i,t}) + \sum_{m=1}^M \beta_m X_{m,i,t} + \varepsilon_{i,t+j} \quad (1)$$

where $\varepsilon_{i,t+j}$ is assumed to follow an *iid* distribution with zero mean and constant variance.

I assume that there is some inertia in credit growth and include therefore the lagged dependent variable as a regressor. Controlling for the impact (β_m) of autonomous factors ($X_{m,i,t}$), the empirical response of credit growth is given by two types of coefficient:

(i) For given values of the regressors with no individual dimension (such as volatility or duration) the response of the average bank's outstanding credit is given by the marginal effect (β_s) induced by a change in money market rates, either observed, expected or VAR model-based ($R_{s,t}$).

(ii) The sensitivity of credit growth to monetary policy is driven by the interaction of *precautionary* and *diversification* supply factors ($X_{k,i,t}$) with the indicator of monetary shock. This interaction effect is captured by the coefficient (β_k) of the product $R_{s,t} X_{k,i,t}$. The total marginal impact of $R_{s,t}$ on $\Delta \log L_{i,t+j}$ is therefore given by the compounded coefficient $\beta_s + \sum_{k=1}^K \beta_k X_{k,i,t}$.

Regardless of the approach to the BLC, average lending growth is expected to be negatively correlated with lagged changes in the monetary stance. In turn, if a given interaction coefficient β_k appears to be significantly negative (positive) then the corresponding variable can be considered as an amplifying (mitigating) supply factor of monetary shocks.

¹⁹Only the change in the coefficient of required reserves was introduced without lag, as it appeared to affect credit growth particularly in the contemporaneous semester/quarter.

Yet, a significant $\beta_s < 0$ is not enough to prove the existence of the BLC, as it may arise from a downward shift in the demand for loans.

In order to solve this identification problem, empirical studies using panel datasets usually check whether there is some heterogeneity in banks' responses. As in the standard precautionary approach, I test whether some interaction factors β_k related to bank-specific characteristics are significant. A priori, banks with relatively higher size, liquid assets, capitalization and long-term borrowing ratios, as well as public and foreign banks, are more likely to overcome liquidity constraints and thus better insulate their lending supply in the case of a monetary tightening. Therefore the corresponding β_k are expected to be positive for the *precautionary* variables. Moreover, the standard approach concludes that the BLC is active only if these interaction coefficients are significant, as heterogeneous bank responses are supposed to signal a shift in supply. Still, this identification strategy has several drawbacks. My specification seeks to address these.

Firstly, bank characteristics are an imperfect proxy for the liquidity constraints that banks face. In order to better capture market discipline I computed and added to the specification a measure of the effective external finance premium (*EFP*) faced by each bank (see above). The variable *EFP* is expected to amplify the response of constrained banks, so its β_k should be negative.

Second, the *precautionary* factors used by the standard approach affect a bank's response to the extent that they capture its ability to overcome only a liquidity risk. To address this shortcoming I extend the analysis from a *diversification* point of view: banks are assumed to jointly manage other risks when reacting to an expected or an observed monetary shock. As long as they can be assessed, the ex ante potential gains/losses tend to amplify a bank's response to shocks. The higher the sensitivity of the value of the bond portfolio to a change in short-term interest rates (captured by the duration of public marketable securities), the larger the potential losses for the bank in the event of a monetary tightening. Therefore the coefficient of *Duration growth* is expected to be negative. In turn, factors that undermine a bank's ability to assess risk scenarios, related to uncertainty, tend to mitigate their response to expected shocks. The variable *Volatility* should therefore exhibit a positive coefficient. Non-performing loans can either capture a bank's willingness to take ex ante risks on its credit portfolio or else increased uncertainty in the credit market. Thus the sign of the coefficient for *NPL ratio* is a priori undetermined.

Third, in the standard empirical literature it is generally assumed that the demand for loans is homogeneous whatever the bank type. In order to control for demand, growth and inflation are usually added as scaling variables. However, it is quite plausible that each bank category faces a differentiated segment of demand for credit. I address this issue through a microfounded strategy of identification: the various regressions seeking to identify the BLC, assumed to be supply-driven (the columns (1) to (7) in Tables 2, 5, 6 and 7) are run only for observations in which the time-varying and bank-specific variable *DemandL* is constrained to

be zero. Thereby, relative to the unidentified regression generally used in the standard literature (column (8)) roughly half of the observations are dropped. For the sake of comparison, the estimation (9) seeks in turn to identify demand-driven changes in credit growth, keeping only observations for which *DemandL* is one.

Lastly, aside from the interaction factors, some control variables are included in every specification.

The required reserves ratios (*RRT*) have been actively used by Brazilian authorities in some periods (e.g. before 2003 and after 2008).²⁰ Yet variations in *RRT* cannot strictly be considered a monetary shock: unlike money market rates, they do not arise from changes in the supply of base money. Therefore, I included them as a control variable, as they affect lending supply by raising the opportunity cost of issuing deposits. The bank-specific *NPL* ratio is also introduced as a scaling variable, to the extent that it influences the bank's perception of the risks in its credit market segment.²¹ In turn, GDP growth and inflation are generally included in empirical studies to control for (homogeneous) demand for loans. Moreover, the inclusion of inflation helps avoid overestimating the effect of the remaining variables on credit growth. As all equations are specified in terms of variation, it is not necessary to deflate either nominal credit growth or nominal variables related to the bank financial structure by a price index (Kashyap & Stein, 1995; Sevestre, 1997). Finally, I introduced two time dummies in 2008 Q2 and Q3, to capture the abnormal uncertainty around the Lehman failure episode, and three seasonal dummies.

4 Estimation and main results

For the sake of comparability, I used the very same specifications and estimation methods to analyze the lending response regardless the measure of the monetary shock or the sample of banks. Along with the estimates, tables report related diagnostic tests.²²

The baseline equation (in Tables 2, 5, 6 and 7) is estimated through pooled Ordinary Least Squares (OLS) in column (1). Namely, the specification assumes that the time-invariant constant C is common to all banks. Using pooled OLS, I also estimated alternative specifications including only either the *precautionary* factors, which corresponds to the usual baseline model in the empirical literature (column (2)), or else the *diversification* ones plus the variable EFP that I computed as a proxy for liquidity constraints (column (3)).

Alternatively, to take into account some structural cross-sectional heterogeneity in the pattern of credit

²⁰See for example De Carvalho & Azevedo (2008).

²¹It may be argued that a significant rise in credit growth might be correlated with a contemporaneous increase in credit risk due to a loosening in lending standards by banks. The inclusion of the variable *NPL ratio* with a lag helps prevent the risk of such an endogeneity bias.

²²From control variables, only the coefficients of required reserves and GDP are presented in the tables. The remaining ones can be made available upon request.

growth, a fixed effects (FE) model was estimated (column (4)). The latter assumes that part of the unobserved error term ($\varepsilon_{i,t} = c_i + v_{i,t}$) is time-invariant but varies across banks.²³

A potential issue arises, as in dynamic models such as (1) the lagged dependent variable included as a regressor is correlated with the cross-section specific part of the perturbation (c_i). This may give rise to the so-called dynamic panel bias (Nickell, 1981). While this is an issue for panels with large N and short T , the bias tends to be nil as the time dimension is long, as in the current sample ($T = 61$ periods). Yet, along with the full sample period, I investigate the extent to which the drivers of the BLC may have changed around the onset of the global financial crisis. I therefore estimate the baseline specification for two time sub-samples: the pre-crisis period until 2007 Q2 (6) and the post-crisis period from 2007 Q3 onwards (7). As the number of quarters is reduced when splitting the sample, particularly in the second period, I estimate (6) and (7) through the system-GMM estimator outlined by Arellano & Bover (1995) and fully developed by Blundell & Bond (1998) to correct the dynamic panel bias. As instruments of the potentially endogenous variable ($\Delta \log L_{i,t-1}$) I use its lagged realizations, both in levels and in differences, as well as the exogenous regressors in levels. Along with the number of instruments used, tables report the p-value of the Hansen J-statistic test for over-identifying restrictions (which checks the null hypothesis that instruments can be considered exogenous as a group) and of the Arellano & Bond (1991) AR(2) test (checking the null hypothesis that errors are not serially correlated in levels).²⁴ In column (5) I also estimated through system-GMM the full sample period for the sake of comparability. In all estimation methods, standard errors used to compute t-statistics are robust to panel-specific autocorrelation and heteroskedasticity.

The main results (Tables 2, 5, 6 and 7) tend to confirm the pertinence of the extended analysis proposed here with respect to the standard empirical tests of the BLC.

4.1 Baseline results on supply-driven credit

Supply-driven regressions estimated over the full sample period (columns (1)-(5)) yield the following results: supply-driven lending growth is significantly negatively correlated with rises in the money market rate.

²³The FE regression amounts to estimate by OLS the pooled model (1) replacing individual observations by their deviation relative to the cross-section mean throughout the sample period T , and adding N individual dummy variables (*Least Square Dummy Variables*, or LSDV). Thereby, the estimators β_k capture the regressors' variability over time within individual banks, while the whole time-constant variability across individuals is captured by individual FE, c_i . The joint significance of individual dummy variables was checked through cross-sectional Fisher and Chi-square tests. Both tests rejected the redundancy of individual effects, so FE estimations (column (4)) are to be preferred to pooled OLS

²⁴In the "difference-GMM" estimator proposed by Arellano & Bond (1991), potentially endogenous regressors specified in differences are instrumented by their past levels. However, as highlighted by Blundell & Bond (1998), levels may be poor instruments when changes in the instrumented variable over time are difficult to predict. Arellano & Bover (1995) propose a "system-GMM" that adds the original equations in levels instrumented by past first differences to the system of first-differentiated equations (see Roodman (2006) for an insightful discussion). To be as consistent as possible across estimations, in the baseline and robustness regressions I generally used as instruments all the available past lags of lending in levels (in the differences equation), and a single lag for lending and the exogenous regressors in differences (in the levels equation). Only twice, in Tables 5 and 7, I reduced the number of lags used as GMM instruments in order to get valid exogenous regressors as a group, or to avoid excessive serial correlation.

This suggests that the BLC has been active on average in 1995-2012.²⁵ Yet, the bank response does not differ according to the bank-specific characteristics usually employed in the literature to capture liquidity-constraints. Within a 90% confidence level, the coefficients of interaction of the precautionary factors with the short-term interest rate are not significant over the whole period, except long-term borrowing in the FE regression. Banks with relatively higher long-term borrowing ratios tend to mitigate their response to observed shocks once individual time-constant effects are taken into account, which suggests that they are able to better overcome liquidity constraints. As for the interaction factors that I added, with the exception of the NPL ratio, the coefficients are generally significant and their signs consistent regardless of the estimation. The coefficient of the bank-specific EFP is significantly negative across regressions (1)-(4), suggesting that banks facing higher market discipline, as measured by this proxy, tend to enhance the BLC. In all regressions (1)-(5), the negative impact on lending growth of observed changes in money market rates is amplified by the duration of bonds and (to a greater extent) mitigated by the volatility of rates. The estimated response to a monetary shock in specification (2), where only the standard precautionary factors are included, is much lower than in regressions (1) and (3)-(5). A plausible interpretation is that, on average for the whole sample period, the set of diversification factors driven by volatility (the coefficient of which is consistently positive and higher in absolute value than that of duration and EFP), has an attenuating effect on the BLC. In other words, rather than capturing the effect of an average quarter, the apparently smoother bank response in regression (2) is likely to be driven by periods of high volatility, omitted among the regressors. Therefore, even when the supply of credit is identified, omitting EFP and the diversification variables may lead to an underestimation of the lending response to monetary shocks. The estimated importance and determinants of the BLC change dramatically as the sample is split into sub-periods around the onset of the global financial crisis. The results suggesting that the average bank has been responsive to monetary shocks over the whole sample are mainly driven by the pre-crisis period. Before 2007 Q3 (estimation (6)), the coefficient of the monetary shock is significantly negative and its value (-1.67%) slightly higher than that estimated through an equivalent method (system GMM) for the whole sample period (-1.55%). Interestingly, prior to the crisis there is no heterogeneity in the responses related to bank-specific constraints. Only the volatility of short-term rates, a common variable, appears to have a (mitigating) effect on bank responses. By contrast, when estimated from 2007 Q3 onwards (column (7)), the effect of the short-term market rate on lending growth is not statistically different from zero. Yet the coefficients of two precautionary variables (size and long-term borrowing) are significantly positive, while those of two diversification variables (EFP and duration) are negative. This suggests that, in the post-crisis period, the BLC has weakened for the average bank, while small banks, those with relatively less

²⁵Credit supply growth shows some positive autocorrelation, suggesting some persistence in lending. Only in GMM estimation is it not significant. As [Nerlove \(2005\)](#) points out, the coefficient of the lagged explained variable is strongly dependent on the estimation method and can even take negative values.

access to long-term funds, and banks facing higher EFP significantly reduce their lending in response to a monetary tightening. Along with financial constraints and market discipline, higher market risk captured by the duration of public bonds appears to strongly amplify the bank response to a given monetary shock.

4.2 Demand identification

I assess the identifying strategy for disentangling loan demand from supply in two ways.

First I estimate a fixed effects model such as (4) using: (i) all the observations, which yields the estimation of the determinants of observed credit in regression (8) (determined by both supply and demand); (ii) only observations for which DemandL=1, which corresponds to the demand-driven lending regression (9). Then I check the extent to which they behave differently from supply-driven loan growth, focusing especially on two variables: (i) lagged GDP growth, which is the variable broadly used in the literature to control for loan demand; (ii) the compulsory reserves ratio (RRT), which is supposed to discourage the bank transformation of deposits into credit and thus to affect only loan supply. Note that, over the whole period, observed and demand-driven variations in lending are negatively correlated with changes in money market rates. Moreover, while the coefficient of the equivalent supply-driven estimation (4) is a bit higher than that of observed lending (8), it cannot be considered statistically different when carrying out a Wald test. This evidences that, as the short-term rate goes up, the contraction of the demand for loans has similar magnitude to that of the loan supply. Yet, this does not necessarily mean that demand is misidentified. On the one hand, lagged GDP growth shows a strong positive correlation with credit growth in regression (9) and, to a lesser extent, in (8), while it is not statistically significant in supply-driven regressions (1) to (6). On the other hand, the required reserves coefficient appears to negatively affect lending in supply-driven regressions for the whole and the pre-crisis sample periods, while RRT is positively correlated with demand-driven credit growth. The variable RRT is specified without lags since it immediately affects bank behaviour. While its negative coefficient in estimations (1) to (6) captures an opportunity cost discouraging credit supply, its positive effect in estimations (8) and (9) may signal a reverse causality: in some periods, Brazilian authorities are likely to raise reserve requirements as soon as they detect upward shifts in the demand for credit.²⁶

Second, seeking to corroborate this identification hypothesis, I use two indexes for credit demand in Brazil (base 2008 =100). Made available by Serasa Experian since 2007 Q1, these indicators are based on an exhaustive monthly survey of loan requests by consumers and firms. Controlling for bank-specific fixed effects and seasonality, and using my cross-sectional and time varying variable DemandL as an

²⁶Contrary to supply-driven lending, credit in regression (9) appears to be negatively autocorrelated. Unlike credit supply, more prone to boom and busts, the demand for loans is more likely to increase when it has declined in the previous period. This lack of persistence may be related to some countercyclical pattern of credit demand. As pointed out by [Bernanke & Gertler \(1995\)](#), households and firms may use bank credit to smooth the impact of variations in income on spending.

identifying condition, I regress credit growth of both the 68 and 90 banks panels on the quarterly variation of Serasa indexes. Tables 3 and 4 show the results. Credit growth conditional on DemandL = 1 is positively and significantly correlated to the loan requests indicators of both consumers and firms in the contemporaneous and past quarter, and up to two lags in most cases, while supply-driven credit barely shows significant correlation. This suggests that my micro-founded strategy manages to disentangle demand from supply in the credit market. It is noteworthy that in demand-driven regression (9), none of the interaction factors is significant, with the exception of foreign ownership. While the response of foreign banks' credit supply is not significantly different from that of their domestic peers, I find that the loan demand they face is relatively less responsive to monetary shocks. This a priori puzzling result can be explained by the strategies of internationalization of global and regional banks, often based on a "follow your client" approach that seeks to exploit informational advantages and long-term relationships with customers (Committee on the Global Financial System, 2014). This may have led branches of foreign banks in Brazil to face specific demand segments, involved in international activities and less sensitive to domestic monetary policy (see for example Cetorelli & Goldberg, 2012).

4.3 Robustness checks: using the large sample of banks and alternative measures of the monetary policy stance

As a first sensitivity test, I investigate the extent to which the results on the BLC in Brazil depend on the sample of banks used. Instead of removing banks that show an abnormal rate of credit growth relative to the cross-sectional average in a given quarter, I remove only these observations. I therefore run the whole set of regressions on the 90 banks "broad" panel expunged from outliers, which involves including a number of foreign banks that were initially discarded. The results (Table 5) are qualitatively very similar to those obtained on the 68 banks panel. The supply-driven lending response of the average bank once I control for specific fixed effects (regression (4)) is slightly stronger (-1.7%). Again, no precautionary factor appears to be consistently significant over 1995-2012. In the sub-period after 2007 Q3, only bank size still appears to be a dampening factor, while the access to long-term borrowing is no longer significant as a driver of the BLC. The main change being that, while the bank supply response is no longer amplified by the EFP over the long period (only in the post-crisis interval), the demand for loans is. As far as depository institutions tend to pass rises in the cost of funds to borrowers, this finding can be interpreted as evidence that banks in the broad sample face on average a more procyclical demand for loans than in the restricted sample (see for example Bernanke & Gertler, 1995).

Next, I test alternative measures of the monetary policy stance. As in my baseline estimations, most of the empirical literature use changes in the short-term rates as a measure of observed monetary shocks.

Yet, the latter encompass an expected and an unexpected part, along with an endogenous component. First, I estimate the extent to which the expected part of a monetary shock affects bank lending responses and its determinants. In order to do so I use the series of expectations that I built as described above. The estimates in Table 6 show that an expected monetary tightening also leads to a credit supply slowdown (although the bank response is of lower magnitude than that to an observed shock).²⁷ The main results on the drivers are consistent with those obtained for observed shocks. Only GMM estimation tends to yield poor results over the long period. But given the number of quarters, the dynamic panel bias is likely to be nil, so that fixed effects estimation remains reliable and is more efficient than system-GMM. The enhancing effect of the EFP remains significant when estimated through OLS over the full sample period (both for supply and demand-driven responses), but does not hold in the GMM estimation of the sub-periods. Precautionary factors do not appear to constrain bank credit supply responses, even in the post-crisis period, while credit demand faced by foreign banks remains less responsive to monetary shocks than that of domestic institutions.

Second, since observed changes in short-term rates are likely to entail an endogenous component, estimations may overstate the response of lending. In my baseline regressions short-term rates and lending growth might be simultaneously determined by the error term. The latter includes, among others, the response of monetary authorities to the economic cycle (e.g. interest rates can be raised in response to a credit boom), which could give rise to spurious results. To check the robustness of my baseline results, I derive an exogenous measure of monetary policy using the residuals of a Vector Autoregressive (VAR) model that describes the dynamic relations of short-term rates with the main macroeconomic variables in the economy. This type of measure, pioneered by [Bernanke & Blinder \(1992\)](#) and further discussed and developed by [Bernanke & Mihov \(1998\)](#), has been recently used in the analysis of the BLC, e.g. by [Olivero et al. \(2011a\)](#) and [Cetorelli & Goldberg \(2012\)](#). I estimate a 2 lag VAR using the following six variables: log of GDP index, log of inflation index, short-term interest rate (Selic), log of outstanding aggregate credit, log of monetary base, and log of nominal exchange rate against USD. Applying this Cholesky ordering for identifying shocks I assume, as in [Bernanke & Blinder \(1992\)](#), that monetary authorities can observe and react to changes in output and inflation within the same quarter, while real variables respond to financial ones with at least a quarter lag.²⁸ Then I use the residuals of the interest rate equation in first differences. Thereby I obtain "primitive" monetary shocks (MP) uncorrelated with the rest of the variables, thus a priori expunged from the endogenous cycle-related component. The results (Table 7) are quite consistent with those obtained in the baseline estimations. While the magnitude of the estimated response of the

²⁷Using the R and ER series, I also estimated the baseline equation decomposing the observed monetary shock into the expected and the unexpected part (results not reported here). While most interaction factors are not significant, the estimation shows that the response of the average bank is more driven by the unexpected component of the observed shock.

²⁸Using a measure of monetary shock obtained by changing the ordering between short-term rates and real variables, and alternative variables such as the real or the effective exchange rates does not significantly change the results on the BLC.

average bank tends to decrease to some extent, the significance and the sign of the coefficients of the factors affecting the BLC generally hold. Among the precautionary factors, only the access to long-term borrowing appears to attenuate the supply response, and rather in the post-crisis period (while size is no longer significant). Leaving aside the GMM estimation of the post-crisis period (7), which yields in general poor results for alternative measures of monetary stance, the significance and the sign of the coefficients of duration and volatility remain robust regardless of the specification. The EFP tends also to be significant, although its sign does not appear to be consistent across regressions. Lastly, using the VAR-based measure of monetary policy lowers the significance of the loan demand "stickiness" faced by foreign banks.

5 Conclusion

Empirical evidence on the factors driving the bank lending channel (BLC) is mixed. Among others, inconclusive results in the empirical literature stem from two challenging issues: (i) the difficulty in disentangling lending supply from credit demand shifts and (ii) an incomplete specification of risks faced by banks when responding to monetary shocks. The latter relates to the inability to take into account the role played by unobservable factors, such as expectations or risk premiums. This paper contributes to addressing these issues. I propose two main extensions to the standard approach generally followed by the econometric studies on the BLC, and test them for the case of Brazil between 1995 and 2012.

Firstly, I compute a proxy for the lending interest rates and use it jointly with the variations in outstanding credit to identify periods in which credit growth was driven by supply at the individual bank level. This method makes it possible to estimate the importance and the drivers of the BLC using only supply-driven observations, as well as comparing results with demand-driven regressions of credit growth. Two main types of test corroborate the validity of this identification scheme. The first is related to the distinct role of control variables in the BLC estimations. GDP growth, which is broadly used in the empirical literature to control for loan demand, is positively and strongly correlated with credit in demand-driven regressions, while it is hardly ever significant in supply driven estimations. By contrast, the coefficient of compulsory bank reserves has a significantly negative impact on credit in supply-driven regressions, whereas it shows a positive correlation in demand-driven estimations (indicating some possible reverse causality, since monetary authorities are likely to raise reserve requirements as they detect an excess demand for credit). A second test shows that, unlike supply-driven lending, credit growth observations identified as demand-driven are positively and consistently correlated with indicators of loans requests, based on an exhaustive survey carried out in Brazil since 2007. This holds both for consumer and firm loan requests, irrespective of the sample of bank credit used.

Secondly, along with the standard variables traditionally used in the literature to take into account the

heterogeneity in bank responses, which I call *precautionary* factors (size, liquid assets, capitalization ratios, and ownership structure), I test a *diversification* approach to investigate whether diverse types of uncertainty other than liquidity risk play a role in the BLC. In the case of Brazil, I find evidence that the lending supply is significantly more sensitive to changes in money market rates when banks face a higher ex ante systematic market risk (captured by the duration of marketable public securities) and a lower volatility of market rates. Moreover, I construct a proxy for the bank-specific external finance premium (EFP). I generally find that, unlike the standard *precautionary* factors, the EFP enhances to some extent the sensitivity of lending supply to monetary shocks.

Robustness was checked applying different estimation methods, enlarging the sample of banks, and using other measures of the monetary policy stance, such as expectations of short-term rates and the exogenous component of a monetary shock drawn from a VAR model. The effect of bond duration and volatility and, to a lesser extent, of EFP, remains consistent across estimations over the long period. In turn, splitting the time sample around the onset of the global financial crisis yields significant contrasts. Interestingly, from 2007 Q3 onwards, the money market rate does not appear to affect the lending supply of the average bank anymore, suggesting some ineffectiveness of monetary policy through the BLC. Yet banks of a relatively smaller size, with less access to long-term funds, and facing higher EFP have become more sensitive to monetary shocks in the post-crisis period. This post-crisis heterogeneous behaviour is not robust across estimations, though. In general common factors remain the main drivers of the BLC in Brazil. Particularly, volatility tends to dampen it in the pre-crisis era, while the duration of public securities enhances lending responses in the post-crisis period.

At least in the Brazilian case, the results found in this paper have some policy implications: providing a context for more stable and easily predictable money market rates and lengthening the maturities of public debt could help unclog an important transmission mechanism of monetary policy.

The lack of significance of standard precautionary factors over the long period can be interpreted through the lens of the main features of the Brazilian banking system, traditionally characterized by significant concentration and high ratios of own funds and securities. A proxy of market discipline computed directly from implicit deposit interest rates tends to better capture the constraints faced by banks when facing a monetary shock than size, liquid assets or capitalization ratios. In turn, part of my findings have more general scope, as they suggest that factors related to market risk and volatility are likely to influence bank asset-liability management and thereby the supply-driven credit responses to monetary shocks. Investigating the effectiveness of the approach proposed in this paper to identifying supply-driven credit shifts and the role of non-liquidity risks in the BLC in other countries provide interesting avenues for future research.

Table 2: Credit growth response to a change in the money market rate (ΔR)

	OLS pooled			Supply-driven			Pre-crisis -GMM			Observed			Demand-driven		
	(1)	(2)	(3)	FE (4)	GMM (5)		(6)	(7)		FE (8)			FE (9)		
Loans growth(-1)	0.188*** (4.54)	0.186*** (4.98)	0.180*** (4.48)	0.148*** (3.76)	0.0188 (0.24)		0.00418 (0.05)	0.0465 (0.61)		-0.0556 (-0.75)			-0.237*** (-2.92)		
$\Delta R(-1)$	-1.243*** (-3.36)	-0.346** (-2.03)	-1.196*** (-3.54)	-1.431*** (-3.87)	-1.546** (-2.43)		-1.666*** (-3.92)	3.012 (0.70)		-1.289*** (-4.43)			-1.443** (-2.35)		
$\Delta R(-1)*\text{Liquidity}(-1)$	-0.00805 (-0.93)	-0.00582 (-0.71)		-0.00681 (-0.91)	-0.00818 (-0.96)		-0.00475 (-0.57)	0.0199 (0.43)		-0.00999 (-0.91)			-0.0320 (-1.22)		
$\Delta R(-1)*\text{Size}(-1)$	0.0842 (1.10)	0.0293 (0.46)		0.0966 (1.34)	0.0497 (0.46)		0.0292 (0.34)	0.667* (1.84)		0.0953 (1.13)			0.252 (1.33)		
$\Delta R(-1)*\text{Capital}(-1)$	-0.000441 (-0.03)	-0.0114 (-0.99)		0.00400 (0.28)	0.00651 (0.23)		0.00741 (0.42)	0.118 (1.07)		0.00385 (0.24)			0.0233 (0.63)		
$\Delta R(-1)*\text{LT Borrowing}(-1)$	0.0112 (1.30)	0.00938 (1.01)		0.0135* (1.70)	0.00548 (0.47)		0.0121 (1.46)	0.146** (2.49)		0.00785 (1.15)			-0.00107 (-0.10)		
$\Delta R(-1)*\text{Foreign}(-1)$	0.0676 (0.14)	0.538 (0.99)		-0.0709 (-0.16)	0.408 (0.31)		-0.0704 (-0.14)	-1.822 (-0.67)		0.493 (1.10)			1.625** (2.14)		
$\Delta R(-1)*\text{Public}(-1)$	0.111 (0.28)	0.0954 (0.27)		-0.00965 (-0.03)	0.819 (0.26)		0.167 (0.28)	2.083 (0.43)		-0.128 (-0.47)			-0.0625 (-0.13)		
$\Delta R(-1)*\Delta EFP(-1)$	-0.00525*** (-3.81)		-0.00483*** (-3.28)	-0.00401*** (-3.04)	-0.00222 (-1.20)		0.0150 (0.83)	-0.00296* (-1.80)		-0.00129 (-0.49)			-0.0315 (-1.37)		
$\Delta R(-1)*\Delta NPL \text{ ratio}(-1)$	0.00930 (0.37)		0.0188 (1.53)	0.0178 (0.69)	-0.00524 (-0.07)		0.00438 (0.10)	0.187 (0.54)		0.0178 (0.66)			0.0380 (0.55)		
$\Delta R(-1)*\text{Duration growth}(-1)$	-0.0116*** (-2.67)		-0.0109*** (-2.61)	-0.0120*** (-2.92)	-0.0111* (-1.95)		-0.00412 (-0.44)	-1.020*** (-2.77)		-0.00388 (-1.00)			-0.000275 (-0.03)		
$\Delta R(-1)*\text{Volatility}(-1)$	0.134*** (3.20)		0.138*** (3.38)	0.157*** (3.40)	0.157** (2.18)		0.166*** (3.39)	-4.927 (-0.64)		0.122*** (3.25)			0.0625 (0.98)		
ΔRRT	-0.851*** (-4.33)	-0.705*** (-3.66)	-0.861*** (-4.25)	-0.866*** (-4.85)	-0.626** (-2.46)		-0.821*** (-4.40)	-0.785 (-1.14)		-0.169 (-1.51)			0.767*** (4.12)		
GDP growth(-1)	0.0495 (0.15)	0.0936 (0.26)	0.114 (0.35)	0.118 (0.42)	0.596 (1.36)		-0.989 (-1.54)	0.773 (1.14)		1.052*** (2.90)			1.718*** (3.39)		
Adj. R-Square	0.117	0.107	0.113	0.110						0.0373			0.0976		
Number of observations	1532	1584	1532	1532	1532		927	605		3257			1725		
Number of instruments					79		56	79							
J-Hansen (p-value)					0.542		0.324	0.781							
AR(2) test (p-value)					0.410		0.133	0.979							

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Credit growth response to a variation in loan requests by consumers (Serasa Index)

	68 banks sample		90 banks sample	
	Supply-driven (1)	Demand-driven (2)	Supply-driven (3)	Demand-driven (4)
Loan requests growth	0.277** (2.61)	0.496*** (3.54)	0.164 (1.63)	0.203** (2.03)
Loan requests growth(-1)	0.0836 (0.78)	0.364*** (3.70)	0.120 (1.02)	0.552*** (5.05)
Loan requests growth(-2)	-0.0733 (-0.65)	0.469*** (3.16)	0.0239 (0.20)	0.323*** (4.15)
Loan requests growth(-3)	-0.198* (-1.93)	0.0788 (1.03)	-0.0105 (-0.10)	0.225** (2.01)
Loan requests growth(-4)	-0.126 (-1.09)	0.0763 (1.04)	-0.0501 (-0.40)	0.00341 (0.05)
Constant	0.473 (0.28)	-3.345* (-1.79)	-0.866 (-0.48)	-4.380*** (-2.64)
Adj. R-Square	0.0316	0.0463	0.0215	0.0560
Number of observations	524	601	687	784

t statistics in parentheses* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Credit growth response to a variation in loan requests by firms (Serasa Index)

	68 banks sample		90 banks sample	
	Supply-driven (1)	Demand-driven (2)	Supply-driven (3)	Demand-driven (4)
Loan requests growth	0.251 (1.66)	0.545*** (4.33)	0.148 (1.00)	0.312*** (3.19)
Loan requests growth(-1)	0.169 (1.43)	0.409*** (3.81)	0.258* (1.84)	0.610*** (4.93)
Loan requests growth(-2)	0.0328 (0.24)	0.157 (1.03)	0.0769 (0.47)	0.351** (2.60)
Loan requests growth(-3)	-0.218* (-1.95)	-0.276 (-1.44)	-0.0207 (-0.14)	0.127 (0.76)
Loan requests growth(-4)	-0.0233 (-0.13)	-0.113 (-0.49)	-0.0600 (-0.30)	-0.0576 (-0.50)
Constant	5.964 (1.32)	9.480** (2.50)	0.204 (0.04)	-2.754 (-0.71)
Adj. R-Square	0.0317	0.0459	0.0257	0.0510
Number of observations	524	601	687	784

t statistics in parentheses* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Credit growth response to a change in the money market rate (ΔR) - 90 banks sample

	OLS pooled			Supply-driven			Pre-crisis -GMM			Post-crisis -GMM			Observed		Demand-driven	
	(1)	(2)	(3)	FE (4)	GMM (5)		Pre-crisis -GMM (6)			Post-crisis -GMM (7)			FE (8)		FE (9)	
Loans growth(-1)	0.135*** (3.48)	0.133*** (3.48)	0.133*** (3.44)	0.103** (2.05)	-0.0334 (-0.52)		-0.0820 (-1.21)			0.108 (1.47)			-0.179*** (-4.13)		-0.380*** (-8.01)	
$\Delta R(-1)$	-1.685*** (-4.22)	-0.161 (-0.97)	-1.643*** (-4.22)	-1.720*** (-4.55)	-1.527*** (-3.44)		-2.454*** (-5.40)			1.069 (0.38)			-1.587*** (-5.39)		-1.084** (-2.27)	
$\Delta R(-1)*\text{Liquidity}(-1)$	0.00642 (0.80)	0.00626 (0.79)		0.00845 (0.98)	0.00848 (0.87)		0.00992 (1.23)			0.000280 (0.01)			0.00456 (0.85)		-0.0123 (-1.18)	
$\Delta R(-1)*\text{Size}(-1)$	-0.0322 (-0.45)	-0.0482 (-0.77)		-0.0165 (-0.23)	-0.0844 (-0.77)		-0.0765 (-0.96)			0.574* (1.84)			-0.0149 (-0.31)		0.0935 (1.19)	
$\Delta R(-1)*\text{Capital}(-1)$	-0.0185 (-1.09)	-0.0287** (-2.30)		-0.0130 (-0.79)	-0.0212 (-1.18)		-0.0175 (-0.98)			0.0283 (0.32)			-0.0191 (-1.60)		-0.0214 (-1.36)	
$\Delta R(-1)*\text{LT Borrowing}(-1)$	0.00388 (0.43)	0.00586 (0.60)		0.00440 (0.51)	0.00567 (0.60)		0.00683 (0.85)			0.0237 (0.42)			-0.00148 (-0.24)		-0.00589 (-0.72)	
$\Delta R(-1)*\text{Foreign}(-1)$	0.345 (0.77)	0.533 (1.09)		0.358 (0.81)	0.314 (0.62)		0.203 (0.46)			1.330 (0.68)			0.737** (2.53)		1.201*** (2.90)	
$\Delta R(-1)*\text{Public}(-1)$	-0.0114 (-0.02)	-0.302 (-0.78)		-0.115 (-0.22)	0.318 (0.39)		0.0870 (0.14)			-1.325 (-0.94)			-0.267 (-0.83)		-0.492 (-1.57)	
$\Delta R(-1)*\Delta EFP(-1)$	-0.00209 (-0.92)		-0.00247 (-1.18)	-0.00154 (-0.82)	-0.00274 (-0.70)		0.00123 (0.68)			-0.00606*** (-3.12)			-0.00314 (-1.40)		-0.0279** (-2.56)	
$\Delta R(-1)*\Delta NPL \text{ ratio}(-1)$	-0.0173 (-0.64)		0.00310 (0.21)	-0.00828 (-0.26)	-0.0338 (-0.67)		-0.0189 (-0.49)			0.0863 (0.40)			-0.00914 (-0.40)		-0.0288 (-0.75)	
$\Delta R(-1)*\text{Duration growth}(-1)$	-0.0120** (-2.47)		-0.0138*** (-2.84)	-0.0118*** (-2.97)	-0.00961** (-2.00)		-0.0119** (-2.55)			-0.838*** (-2.73)			-0.00700*** (-2.15)		-0.00950 (-1.27)	
$\Delta R(-1)*\text{Volatility}(-1)$	0.215*** (4.60)		0.226*** (4.81)	0.219*** (4.75)	0.195*** (3.57)		0.287*** (5.30)			-2.830 (-0.53)			0.186*** (5.22)		0.0890* (1.78)	
ΔRRT	-0.732*** (-4.78)	-0.610*** (-3.99)	-0.786*** (-5.12)	-0.751*** (-5.26)	-0.674*** (-3.92)		-0.860*** (-5.08)			0.528 (0.80)			-0.128 (-1.05)		0.428*** (2.40)	
GDP growth(-1)	0.0793 (0.21)	0.308 (0.76)	0.127 (0.33)	0.197 (0.51)	0.377 (0.89)		-1.089* (-1.70)			0.856** (2.36)			1.153*** (4.24)		1.578*** (4.84)	
Adj. R-Square	0.0846 1941	0.0738 2004	0.0803 1941	0.0817 1941			1156 21			785 79			0.0865 4152		0.209 2211	
Number of observations					1941											
Number of instruments					79											
J-Hansen (p-value)					0.0918					0.184						
AR(2) test (p-value)					0.774					0.361						

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Credit growth response to a change in the expected money market rate (ΔER)

	OLS pooled			Supply-driven			Observed			Demand-driven		
	(1)	(2)	(3)	FE (4)	GMM (5)	Pre-crisis -GMM (6)	Post-crisis -GMM (7)	FE (8)		FE (9)		
Loans growth(-1)	0.206*** (4.88)	0.190*** (5.39)	0.197*** (4.68)	0.169*** (4.30)	0.0206 (0.25)	0.0361 (0.49)	-0.0515 (-0.74)	-0.0469 (-0.61)		-0.226*** (-2.69)		
$\Delta ER(-1)$	-0.800** (-2.31)	-0.296* (-1.82)	-0.756** (-2.29)	-0.777** (-2.23)	-0.471 (-1.05)	-0.834** (-2.61)	0.205 (0.08)	-0.700*** (-3.46)		-0.685 (-1.61)		
$\Delta ER(-1)*Liquidity(-1)$	-0.00381 (-0.51)	-0.00219 (-0.30)		-0.00359 (-0.44)	-0.000584 (-0.07)	-0.00560 (-0.59)	0.0330 (0.68)	-0.00404 (-0.36)		-0.0292 (-1.22)		
$\Delta ER(-1)*Size(-1)$	0.0956 (1.46)	0.0187 (0.32)		0.0880 (1.36)	0.0821 (1.28)	0.0756 (1.08)	-0.156 (-0.28)	0.0985 (1.22)		0.170 (1.17)		
$\Delta ER(-1)*Capital(-1)$	0.000649 (0.05)	-0.0207 (-1.59)		-0.000517 (-0.04)	0.00487 (0.36)	0.00695 (0.51)	0.0421 (0.41)	0.0130 (0.99)		0.0164 (0.66)		
$\Delta ER(-1)*LT Borrowing(-1)$	0.00438 (0.67)	0.00278 (0.36)		0.00571 (0.92)	0.00783 (0.73)	0.00544 (0.76)	0.0187 (0.31)	0.00545 (0.87)		-0.00215 (-0.21)		
$\Delta ER(-1)*Foreign(-1)$	0.303 (0.84)	0.741 (1.51)		0.197 (0.51)	-0.242 (-0.28)	0.322 (0.80)	1.733 (0.49)	0.577 (1.37)		1.271** (2.15)		
$\Delta ER(-1)*Public(-1)$	-0.204 (-0.56)	-0.261 (-0.78)		-0.229 (-0.52)	-0.193 (-0.32)	-0.139 (-0.28)	0.804 (0.23)	-0.230 (-0.99)		-0.0689 (-0.16)		
$\Delta ER(-1)*\Delta EFP(-1)$	-0.00463*** (-3.06)		-0.00438*** (-2.84)	-0.00379*** (-3.18)	-0.000583 (-0.27)	-0.0219 (-1.31)	0.00168 (0.94)	-0.000889 (-0.29)		-0.0468* (-1.95)		
$\Delta ER(-1)*\Delta NPL ratio(-1)$	0.0189 (0.81)		0.0153 (1.02)	0.0174 (0.56)	0.0000137 (0.00)	0.0192 (0.50)	0.0600 (0.21)	0.0282 (1.26)		0.0211 (0.47)		
$\Delta ER(-1)*Duration growth(-1)$	-0.0106** (-2.51)		-0.0101** (-2.41)	-0.00981** (-2.02)	-0.00600 (-0.90)	-0.0192** (-2.02)	-0.384** (-2.24)	0.00198 (0.40)		0.000885 (0.08)		
$\Delta ER(-1)*Volatility(-1)$	0.0885* (1.95)		0.0885* (1.90)	0.0864** (2.15)	0.0713 (1.44)	0.0712* (1.94)	-0.675 (-0.21)	0.0928*** (3.79)		0.0418 (0.80)		
ΔRRT	-0.745*** (-3.70)	-0.703*** (-3.46)	-0.743*** (-3.66)	-0.759*** (-3.81)	-0.601** (-2.38)	-0.493** (-2.09)	-0.738 (-0.85)	-0.232* (-1.89)		0.603*** (3.86)		
GDP growth(-1)	0.544 (1.57)	0.184 (0.54)	0.613* (1.74)	0.648** (2.47)	1.078*** (2.69)	0.555 (0.80)	0.705 (0.76)	1.501*** (3.92)		2.095*** (4.03)		
Adj. R-Square	0.116	0.112	0.113	0.105				0.0338		0.106		
Number of observations	1532	1584	1532	1532	1532	927	605	3257		1725		
Number of instruments					79	56	79					
J-Hansen (p-value)					0.580	0.257	0.788					
AR(2) test (p-value)					0.335	0.131	0.594					

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Credit growth response to a VAR model-based measure of monetary shock (MP)

	OLS pooled			Supply-driven			Observed		Demand-driven
	(1)	(2)	(3)	FE (4)	GMM (5)	Pre-crisis -GMM (6)	Post-crisis -GMM (7)	FE (8)	FE (9)
Loans growth(-1)	0.198*** (4.90)	0.184*** (5.30)	0.191*** (4.80)	0.172*** (4.63)	-0.0144 (-0.20)	-0.345*** (-3.80)	-0.0716 (-0.45)	-0.0474 (-0.64)	-0.235*** (-2.77)
Δ MP(-1)	-0.975*** (-3.27)	-0.0388 (-0.23)	-0.941*** (-3.54)	-1.015*** (-4.11)	-1.362** (-2.38)	-1.407*** (-3.20)	-1.163 (-0.52)	-1.057*** (-3.96)	-1.559** (-2.53)
Δ MP(-1)*Liquidity(-1)	-0.00502 (-0.69)	-0.00374 (-0.54)		-0.00588 (-1.05)	-0.00427 (-0.56)	0.00124 (0.12)	-0.00135 (-0.07)	-0.00736 (-0.75)	-0.0280 (-0.98)
Δ MP(-1)*Size(-1)	0.0883 (1.39)	0.0425 (0.73)		0.0812 (1.51)	0.0585 (0.81)	-0.112 (-0.96)	0.204 (0.57)	0.0889 (1.15)	0.283 (1.37)
Δ MP(-1)*Capital(-1)	0.00398 (0.31)	-0.00270 (-0.30)		0.00133 (0.11)	0.0165 (0.92)	-0.000789 (-0.04)	-0.00112 (-0.02)	0.0155 (1.14)	0.0441 (1.21)
Δ MP(-1)*LT Borrowing(-1)	0.0110 (1.32)	0.0131* (1.69)		0.0109 (1.54)	0.00550 (0.65)	0.00372 (0.34)	0.0807** (2.43)	0.00920 (1.40)	0.00661 (0.65)
Δ MP(-1)*Foreign(-1)	0.0154 (0.03)	-0.0464 (-0.10)		0.00403 (0.01)	0.302 (0.55)	0.463 (0.70)	0.798 (0.66)	0.233 (0.59)	0.793 (1.24)
Δ MP(-1)*Public(-1)	-0.231 (-0.64)	-0.152 (-0.46)		-0.212 (-0.54)	0.0902 (0.12)	-0.129 (-0.15)	1.347 (0.68)	-0.222 (-0.87)	-0.229 (-0.49)
Δ MP(-1)* Δ AFP(-1)	-0.00231* (-1.66)		-0.00215 (-1.56)	-0.00234* (-1.81)	0.00431* (1.90)	-0.00698 (-0.42)	0.00695 (1.22)	0.00407* (1.71)	0.0111 (0.38)
Δ MP(-1)* Δ NPL ratio(-1)	0.0241 (1.11)		0.0181 (1.37)	0.0191 (0.82)	0.0180 (0.42)	0.0242 (0.47)	0.149 (0.74)	0.0306 (1.35)	0.0708 (1.05)
Δ MP(-1)*Duration growth(-1)	-0.0121*** (-3.20)		-0.0114*** (-3.08)	-0.0119*** (-2.93)	-0.0107* (-1.67)	-0.0123* (-1.79)	-0.188 (-1.34)	-0.00430 (-1.05)	0.0101 (0.96)
Δ MP(-1)*Volatility(-1)	0.103*** (3.24)		0.103*** (3.27)	0.107*** (3.43)	0.154** (2.57)	0.150*** (2.93)	1.931 (0.66)	0.115*** (4.00)	0.120* (1.69)
Δ RRT	-0.847*** (-4.40)	-0.814*** (-4.22)	-0.852*** (-4.38)	-0.898*** (-4.98)	-0.662*** (-3.15)	-0.620*** (-3.13)	-0.886 (-1.17)	-0.260** (-2.24)	0.602*** (3.83)
GDP growth(-1)	0.165 (0.49)	0.299 (0.89)	0.237 (0.70)	0.232 (0.87)	0.746* (1.69)	1.282 (1.42)	1.233* (1.84)	1.198*** (3.18)	1.780*** (3.42)
Adj. R-Square	0.121	0.108	0.118	0.116				0.0342	0.0869
Number of observations	1536	1563	1536	1536	1536	929	607	3262	1726
Number of instruments					79	55	79		
J-Hansen (p-value)					0.603	0.300	0.623		
AR(2) test (p-value)					0.384	0.102	0.359		

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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Appendix

A Estimation of the interest rates expectations

The aim of this section is obtaining measures that capture both the expectations and the degree of uncertainty over short-term interest rates (Selic) during the period 1995-2012. The data corresponding to the consensus market forecast of the Selic rate in Brazil are only available from November 2001 onwards. This information is gathered by the Banco Central do Brasil (BCB) via a survey conducted on the main participants in the money market. Being the market expectations data unavailable between 1995 and 2001, I carry out a simulation drawn from ARIMA univariate estimations for this period.²⁹ Within the different forecasting methods, univariate models - popularized by the pioneer work of [Box & Jenkins \(1976\)](#), are widely used as a reference to forecast short-term nominal variables. These models consist of a statistical inference of the variable forecasted through the characteristics of the time series and of the forecast errors observed in the past. The most parcimonious univariate specifications (random walk, ARIMA) have often shown a better capacity to forecast nominal financial variables than multivariate models or structural equation models based on theoretical relations ([Meese & Rogoff 1983](#); [Sarno et al. 2005](#)).

A.1 Data and periods of estimation and forecast

Nominal interest rate series are used over two fixed-length subsets: an estimation period and a forecast period. Both move as a "rolling window" from a t date to another so as to simulate an expectation for each $t+j$ date. Each estimation period (in sample) lasts until the current date (t). This period includes all the dates whose interest rates realizations can be observed by banks: $t - n + 1, t - n + 2, \dots, t$. The size of the estimation sample, which includes the t date, is therefore of n observations. Each forecast period (out of sample) follows immediately the current date, from which interest rates realizations cannot be observed: $t + 1, t + 2, \dots, t + j$. The number of months j stands for the forecast horizon length. The ARIMA models were estimated based on the observations of the money market interest rate (the Selic rate). Since it is an overnight rate, for the estimation I used the series of the Selic rate accumulated at the end of the month in monthly percentage (referred to as SELIC). This data are available on the website www.bcb.gov.br (time series No. 4390). The initial estimation period (1991:08-1995:12) precedes the date to which the first expectation is made. The frequency is monthly and the number of observations is $n = 53$. I fixed this size of the sample so as to start the estimation right after the last "heterodox" stabilization plan - the Collor II plan, which lasted until June 1991. Following its failure, the level of the Selic rate took an upward trend and its progression was only interrupted by the Real plan in July 1994.

²⁹Concerning the statistical inference based on time series and forecasting methods of interest rates, I draw mainly on [Hamilton \(1994\)](#).

The window estimation is rolled all the semesters until June 1999, then all the trimesters until the date of the publication of the first survey data on the market forecast (at the end of 2001). I therefore assume that agents revise their expectations based on new observations and newly committed errors. The frequency of estimation-forecast was chosen to simulate the banks' horizon of decision. This empirical horizon (j) is determined by the data for which information about bank financial statements were available (six months until December 1999 and three months from that date onwards). In total, 24 models were identified and estimated, characterizing the behavior of the Selic rate during the 53 months prior to December 1995, June 1996 and so on until September 2001. An additional estimation (numbered 0) has been made for the period 1991:03-1995:06, so as to simulate an expectation in June 1995 six months ahead and the corresponding error observed in December 1995.³⁰ During the forecast period banks, whose decisions are concerned by the future realizations of rates, form their expectations. The forecast $\hat{r}_{t,t+j}$, also referred to as $E(r_{t+j}|I_t)$, denotes the expectation of the interest rate j periods ahead, conditional on the information available at t . Like for the estimation frequency, the forecast frequency of the Selic rate is adjusted to the periods when the banks financial statements are available: thus j corresponds to 6 months for the 9 semesters going from June 1995 to June 1999; then, the forecast horizon is 3 months for the 52 trimesters going from December 1999 to September 2001. The obtained forecast of the Selic rate in monthly percentage based on the ARIMA estimation was in turn converted into an annual rate in order to form a single homogeneous series with the data provided by the survey on the market expectations from December 2001 on.³¹

Before estimating the ARIMA models, the stationarity of series was analyzed. Unit root tests on the money market rate in levels were carried out by decomposing the complete series in 8 periods of 53 months, mutually intertwined and going up December of each year. The goal was to identify possible structural breaks in interest rate series. I thus consider that banks revised every year their perception of the potential effect (temporary or permanent) of a shock on the Selic rate, based on the observed values during the approximately four and a half previous years. In the sample window 1995-1999, which virtually corresponds to the period of quasi-fixed exchange rate regime in Brazil, the short rate series in level (SELIC) appears stationary, i.e. its integration order is $I(0)$. The rest of the periods are characterized by a stochastic trend DS of order $I(1)$, which leads to using those series in first differences (referred to as DSELIC). The order of integration of the Selic rate for Brazil is confirmed by other works analyzing its stationarity. On a monthly frequency, empirical works tend to show that nominal short-term rates follow a process $I(1)$ both for the high inflation period 1985-1994 (Cati et al., 1999) and for the moderate inflation

³⁰This estimation period No. 0 includes 52 months only. Rather than introducing a time dummy (and so losing a degree of freedom), I directly excluded the first date (1991:02), at which the Selic rate registered a sharp fall of 14,17 in monthly percentage due to the Collor II plan. The aim is to prevent this outlier from polluting the estimation of the generating process of the interest rate.

³¹According to the method used in Brazil to annualize the monthly interest rate, the weight of each month in the year differs according to the number of working days on a basis of 252 days per year. For example, in December 1995 the number of working days was of 20. Based on a Selic rate of 2,7773 in monthly percentage, the annual rate is calculated as follows : $(1 + 0.027773)^{(252/20)} = 41.22$ annual rate.

regime 1994-2000 (Minella, 2003). Sales & Tannuri-Pianto (2007) also confirm the existence of a unit root for the period 1994-2004.

According to the stationarity results, the univariate model to be identified and estimated is thus as follows:

$$r_t = \phi_1 r_{t-1} + c + u_t \quad \text{with } \phi_1 < 1, \text{ for the period 1995-99 ;}$$

$$\Delta r_t = u_t \quad \text{for the rest of the periods ;}$$

where u_t is a stationary random process.

A.2 Estimation of the generating process of the interest rate series

The specification of the variable r_t or Δr_t depends on the form of the stationary process u_t : either a white noise (ω) or else some AR and/or MA process of orders p, q . Consider the most frequent case in our sample: the Selic rate series is stationary in differences, following the form $\Delta r_t = u_t$. If the stationary process in differences u_t appears to be a white noise, so that $\Delta r_t = \omega_t$, the interest rate in level follows a random walk, namely a process without memory. In this case, accepting the random walk would imply that, based on the series analyzed during the estimation period, the best forecast for banks one period ahead is the interest rate of the immediately previous month, since $r_t = r_{t-1} + \omega_t$. This forecast, so-called "naive", can eventually imply a constant to estimate if the residual ($\hat{\omega}_t$) is not centered. Unlike a white noise, the random processes AR and MA involve a memory that can be modeled and estimated. If the short-term interest rate in differences follows an ARMA(p, q) process, it can be written:

$$\Delta r_t = \phi_1 \Delta r_{t-1} + \dots \phi_p \Delta r_{t-p} + \omega_t + \alpha_1 \omega_{t-1} + \dots \alpha_q \omega_{t-q} \quad (1)$$

$$\text{with } \sum_{j=1}^p \phi_j < 1$$

With the aim of obtaining precise estimators, I chose to simulate the forecast on the interest rate based on series that go back as early as 53 months. Nevertheless, the capacity to forecast based on long series of past realization can be questioned. This is particularly the case in economies marked by structural mutations and characterized by abrupt and infrequent variations, like Brazil during the period of analysis of the Selic interest rate. Following the main methods of analysis of the serial correlation (Box-Pierce, Ljung-Box), the existence of an extreme value of Δr_t , even if it dates far back in relation to the estimation and forecast period, can lead to accepting the independence of realizations, even though the series has a memory beyond this value. Yet, accepting that the generating process of the short rate series does not have a memory can lead to an underestimation of the model used by agents to make their forecasts. For instance, in forecasting short-term rates in the United States for horizons of several months, Deaves (1996) and Stock & Watson (1998) consider that an ARIMA model shows better performances than the

random walk as long as the integration order $I(d)$ is rightly determined. Working with series of rates in first differences contributes particularly to reduce extreme forecast errors.

The identification of the Selic rate series in differences in Brazil presents this risk of underestimation of the underlying process. Some extreme values can be considered "abnormal" according to the common dispersion thresholds. I therefore introduced time dummies for the dates where the variation of the interest rate is likely to be related to an extraordinary event, as during the Real plan, the crises in south-east Asia (around the end of 1997) and the speculative attack leading to the devaluation of the real (between the end of 1998 and the beginning of 1999). I used D_1 for 94:07, D_2 for 94:08, D_3 for 97:11, D_4 for 98:09 and D_5 for 99:03. Only D_2 , tested for the estimation period No.13 (beginning in August 1994), appeared as non-significant. The remaining D_t proved to be an important part of the explained variability of the Selic rate, both in differences and in levels, during the corresponding periods. The inclusion of these dummy variables permitted pointing out abnormal values and correcting the resulting perturbation over the estimation of the AR and MA parties.

Once the effect of the extraordinary events produced by Δr_t was assessed, the orders p, q of the AR and MA parts of the series were identified. I did it so by eliminating progressively the non-significant coefficients. Departing from an order (p, q) relatively high (4), I sequentially re-estimated the inferior order model, $(p - 1, q)$ or $(p, q - 1)$, whenever the estimator of order p or q could not be accepted to a minimum confidence threshold of 90%. Whenever more than one model seemed valid for a given period, I selected the one whose Akaike and Schwartz criteria showed a lower variance of the sum of the squares of residuals. For each of the 24 models, the hypothesis of homoskedasticity and of serial independence of the errors were accepted both by the tests of White and ARCH and the test of Breusch-Godfrey. The estimators are thus theoretically efficient, i.e. of minimal variance. Whenever the value of the t-stat changes in relation to the model without correction, Table A.1 reports the standard deviation corrected either by the covariance matrix of West (W) -consistent with the heteroskedasticity- or by the matrix of Newey-West (N-W), consistent with autocorrelation.

The expected Selic rate was computed as a six months ahead forecast based on the ARMA estimation of 1995:12. Given that, at this date (t), agents didn't know the realizations in 96:01,...96:05, I calculate a dynamic forecast. Unlike static forecasts, in the dynamic forecast of the interest rate (for example for 96:06), the variations of the Selic rate (Δr_t) and the errors (ϵ) corresponding to the intermediary dates are not the observed realizations but the values estimated at the date $t = 95:12$ (the expected error in subsequent periods being nil in average). This replicates the problem that characterizes forecasts in practice: ex post, the precision of the multi-period dynamic forecast quickly declines with the time horizon.

The expected series of Selic rate were completed, from December 2001 onwards, by the forecasts made from the market survey in order to form the series used as indicator of the expected monetary shock (ER).

Table A.1: Estimation of the Selic rate generating processes and one semester/trimester ahead forecast

Period	of estim.		Estimated variable	Chosen model	Correct autocor heteroc	Time dummies	Constant	Estimated coeff. AR			Estimated coeff. MA				Adj. determ. coeff.	Forecast j months ahead (%/month)
	Date of Forecast	Period					c	ϕ_1	ϕ_2	ϕ_3	α_1	α_2	α_3	α_4	$\bar{R}^2$	$E(r_{t+j} I_t)$
91:2	95:6	0	Δr_t	MA(4)		D_1					0,66 (0,07)	0,25 (0,12)	0,62 (0,08)	0,97 (0,05)	0,94	
91:8	95:12	1	Δr_t	ARMA(1,1)		D_1		0,79 (0,23)			-0,63 ** (0,28)				0,92	3,53
91:11	96:3	2	Δr_t	ARMA(2,2)		D_1		1,18 (0,09)	-0,64 (0,09)		-1,30 (0,08)	0,87 (0,09)			0,95	
92:2	96:6	3	Δr_t	ARMA(1,1)		D_1		0,84 (0,22)			-0,68 (0,27)				0,96	2,50
92:5	96:9	4	Δr_t	ARMA(2,2)		D_1	0,40 * (0,21)	1,03 (0,08)	-0,65 (0,10)		-1,16 (0,05)	1,00 (0,00)			0,97	
92:8	96:12	5	Δr_t	MA(4)		D_1					0,51 (0,04)	0,22 (0,06)	0,47 (0,05)	0,97 (0,03)	0,97	1,77
92:11	97:3	6	Δr_t	ARMA(3,3)		D_1		0,61 (0,11)	-0,54 (0,06)	0,77 (0,08)	-0,47 (0,16)	0,16 (0,11)	-0,75 (0,18)		0,98	
93:2	97:6	7	Δr_t	ARMA(1,1)		D_1		0,93 (0,03)			-0,99 (0,02)				0,97	1,70
93:5	97:9	8	Δr_t	ARMA(1,1)		D_1		0,90 (0,03)			-0,98 (0,02)				0,98	
93:8	97:12	9	Δr_t	ARMA(1,1)		D_1		0,83 (0,04)			-1,00 (0,02)				0,98	2,30
93:11	98:3	10	Δr_t	ARMA(1,1)		D_1		0,96 (0,12)			-1,20 ** (0,55)				0,98	
94:2	98:6	11	Δr_t	ARMA(1,2)		D_1, D_3		-0,80 (0,01)			1,80 (0,11)	0,81 (0,11)			0,99	2,79
94:5	98:9	12	Δr_t	ARMA(2,3)		D_1, D_3	-0,09 (0,02)	-0,48 (0,19)	0,38 (0,12)		0,63 ** (0,26)	-0,95 (0,03)	-0,62 ** (0,29)		0,99	
94:8	98:12	13	Δr_t	AR(1)		D_3, D_4	-0,08 ** (0,03)	0,06 (0,00)							0,76	1,17
94:11	99:3	14	Δr_t	ARMA(1,1)		D_3, D_4, D_5	-0,08 ** (0,04)	-0,72 (0,11)			1,00 (0,13)				0,63	
95:2	99:6	15	Δr_t	AR(1)		D_3, D_4, D_5	0,25 (0,14)								0,51	1,92
95:5	99:9	16	Δr_t	ARMA(2,1)		D_3, D_4, D_5	-0,10 ** (0,03)	-0,57 (0,17)	0,11 (0,06)		1,27 (0,32)				0,77	
95:8	99:12	17	r_t	ARMA(2,2)		D_3^{**}, D_5	1,96 (0,03)	1,53 (0,11)	-0,61 (0,08)		-0,56 (0,18)	-0,44 ** (0,18)			0,85	1,56
95:11	00:3	18	r_t	ARMA(2,2)		D_3^{**}, D_5	1,94 (0,04)	1,64 (0,09)	-0,71 (0,08)		-0,61 (0,20)	-0,35 * (0,19)			0,78	1,97
96:2	00:6	19	r_t	ARMA(1,1)		D_3^*, D_5	1,83 (0,15)	0,69 (0,08)			0,39 ** (0,20)				0,74	1,98
96:5	00:9	20	r_t	ARMA(1,1)		D_3^*, D_5	1,79 (0,17)	0,71 (0,09)			0,39 ** (0,19)				0,75	1,64
96:8	00:12	21	Δr_t	ARMA(3,3)		D_3, D_4, D_5		0,61 (0,16)	0,56 (0,16)	-0,56 (0,18)	-0,73 (0,04)	-0,75 (0,09)	1,46 (0,12)		0,78	1,52
96:11	01:3	22	Δr_t	ARMA(2,2)		D_3, D_4, D_5	-0,08 ** (0,04)	1,16 (0,14)	-0,72 (0,17)		-1,24 (0,07)	0,92 (0,09)			0,60	1,16
97:2	01:6	23	Δr_t	ARMA(1,1)		D_3, D_4, D_5		0,99 (0,03)			-1,00 (0,09)				0,60	0,99
97:5	01:9	24	Δr_t	ARMA(2,2)		D_3, D_4, D_5	-0,09 * (0,05)	1,42 (0,13)	-0,74 (0,17)		-1,51 (0,01)	0,99 (0,02)			0,63	1,09

Note : All coefficients are significant either at 10% (**), 5% (*) or 1%. Standard errors are between brackets.

With the exception of the period December 1999-December 2001, the forecast error of the simulation in relation to the rate effectively observed (R) is quite correlated to the daily volatility of the Selic rate (*Volatility*), used below in the response function (see Figure A.1).

Ultimately, the ARIMA model aims at capturing the evolution of the information about the Selic rate that agents had at the beginning of each semester, then each quarter. I consider that banks use as information past values and forecast realized errors, which amounts to assimilate their forecasts to adaptive expectations (Simon, 1989, p. 6). As Bevilacqua et al. (2008) highlight, in Brazil, it is only after the consolidation of the inflation targeting regime that the authorities have succeeded in anchoring the market expectations over the announced goals. In the period prior to the first publication of the market expectations (November 2001), the past realizations and forecast errors have traditionally determined the formation of the expectations of the Selic rate. The modeling choice described here, which assimilates the rates forecasted by banks to adaptive expectations, seems thus coherent with the stylized facts in Brazil.

Figure A.1: observed and anticipated *Selic rate*, forecast error and volatility

Note : BCB and author's calculations

B Financial statements accounts and sample of banks

From the site: www.bcb.gov.br / *Sistema Financeiro Nacional / Informações cadastrais e contábeis*, the variables describing bank financial statements were constructed using the following COSIF accounts:

Assets

Cash: *Disponibilidades*

Account: 11000006

Securities: *Títulos e valores mobiliários*

Account: 13000004

Interfinancial assets: *Aplicações interfinanceiras*

Account: 12000005

Non-performing loans provisions: *Provisão por créditos em liquidação*

Accounts: 16900008 + 17900007

Gross loans: *Operações de Crédito et arrendamento financeiro + Outros créditos*

Accounts: 16000001 + 17000000 + 16900008 + 17900007 + 18000009

Liabilities

Insured liabilities: *Depósitos à vista + Caderneta de poupança + Depósitos a prazo (CDB) + Outros*

Accounts: 41100000 + 41200003 + 41500002 + 41400009 + 41700008 + 41800001 + 41900004

Noninsured liabilities: *Depósitos interfinanceiros (CDI) + Captações no mercado aberto + Aceites e emissão de títulos*

Accounts: 41300006 + 42000006 + 43000005

Long term borrowing: *Obrigações por empréstimos e repasses*

Account: 46000002

Capital: *Patrimônio líquido*

Accounts: 60000002 + 70000009 + 80000006

Income statements

Interest expenses: *Despesas de captações no mercado*

Comptes: 81100008 + 81980008

Credit income: *Receitas de operações de crédito*

Accounts: 71100001 + 71920009 + 71925004 + 71950000 + 71980001 + 81945005 + 81950007

Table B.1: Summary of the backwards integration of banks financial statements

Brazil 1995-2012: banks included in the initial sample (I)Source: the author from Banco Central do Brasil / *Evolução do SFN/ Anexos* (site www.bcb.gov.br), Nakane and Weintraub (2005), Makler (2000), Ness (2000)

Ownership: 1 = public or state bank; 2 = private domestic bank; 3 = foreign bank

(1) Information as for September 2012

Name of the bank or conglomerate (III) included in the initial sample	Observation period	Abbreviated name	Other usual denominations	Rank according to assets size (1)	Capital ownership (1)	Independent or Conglomerate (1)	Banks (II) under the control of the bank (III)	Banks (I) previously under the control of bank (II)	Rank according to assets size (1)	Capital ownership (1)	Date of transfer of control
ABC-BRASIL	Dec 95 - Sep 12	ABC	ABC-ROMA, ROMA	24	3	C					
ALFA	Dec 99 - Sep 12	ALFA		21	2	C					
ARBI	Sep 01 - Sep 12	ARBI		92	2	I					
AZTECA	Mar 08 - Sep 12	AZTE		94	3	I					
BANCAP	Dec 95 - Sep 12	BCAP		99	2	I					*
BANCNACION	Dec 95 - Sep 12	BNAC	Banco de la Nacion Argentina	89	3	I					
BANCO TOPAZIO	Jun 09 - Sep 12	BTOP		78	2	I					
BANCOOB	Dec 97 - Sep 12	BCOO	Banco Cooperativo do Brasil	22	2	C					
BANESE	Dec 95 - Sep 12	BNSE	Banco do Estado de Sergipe	49	1	I					
BANESTES	Dec 95 - Sep 12	BSTE	Banco do Estado do Espirito Santo	31	1	C					
BANIF	Dec 95 - Sep 12	BANI	Banco Internacional do Funchal	54	3	C	PRIMUS		107	4	Dec-99
BANPARA	Dec 95 - Sep 12	BPAR	Banco do Estado do Pará	44	1	I					
BANRISUL	Dec 95 - Sep 12	BSUL	Banco do Estado do Rio Grande do Sul	11	1	C					
BANSICREDI	Jun 96 - Sep 12	BSDI	Banco Cooperativo Sicredi	23	2	I					
BARCLAYS	Dec 97 - Sep 12	BARC	BARCLAYS Galicia	36	3	C					
BASA	Dec 95 - Sep 12	BASA	Banco da Amazônia	29	1	I					
BASEMSA	Mar 06 - Sep 12	BASE	Bancop Semear	74	2	I					
BB	Dec 95 - Sep 12	BB	Banco do Brasil	2	1	C	BEPI		77	1	Dec-08
							BESC		31	1	Jan-09
							NOSSA CAIXA		9	2	Mar-09
BBM	Jun 98 - Sep 12	BBM		48	2	C					
BCGB	Jun 09 - Sep 12	BCGB	Banco Caixa Geral Brasil	63	3	C					
BCOMURUGUAI	Jun 97 - Sep 12	URUG	Banco Comercial Uruguai	80	3	I					
BEXS	Mar 11 - Sep 12	BEXS	Didier Levy	96	2	C					
BIC	Dec 95 - Sep 12	BIC	Banco Industrial e Comercial	18	2	C					
BMB	Dec 95 - Sep 12	BMB	Banco Mercantil do Brasil	27	2	C					
BMG	Dec 95 - Sep 12	BMG		16	2	C	GE CAPITAL		80	4	Aug-11
							SCHAHIN		47	3	Aug-11
BNB	Dec 95 - Sep 12	BNB	Banco do Nordeste do Brasil	14	1	I					*
BNP PARIBAS	Dec 95 - Sep 12	BNP	Banque Nationale de Paris	20	3	C	BGN		44	3	Dec-06
BOC	Sep 09 - Sep 12	BOC	Banco Of China Brasil	73	3	I					*
BONSUCESSO	Jun 98 - Sep 12	BONS		45	2	C					

Brazil 1995-2012: banks included in the initial sample (II)

Source: the author from Banco Central do Brasil / *Evolução do SFN/ Anexos* (site www.bcb.gov.br), Nakane and Weintraub (2005), Makler (2000), Ness (2000)

Ownership: 1 = public or state bank; 2 = private domestic bank; 3 = foreign bank

(1) Information as for September 2012

Name of the bank or conglomerate (III) included in the initial sample	Observation period	Abbreviated name	Other usual denominations	Rank according to assets size (1)	Capital ownership (1)	Independent or Conglomerate (1)	Banks (II) under the control of the bank (III)	Banks (I) previously under the control of bank (II)	Rank according to assets size (1)	Capital ownership (1)	Date of transfer of control	
BRADESCO	Dec 95 - Sep 12	BRAD		3	2	C	BCN		14	3	Dec-97	
								CREDIREAL	63	4	Aug-97	
							PONTUAL		33	3	Sep-98	
							BANEB		31	2	Jun-99	
							BOAVISTA		24	4	Sep-00	
							BEA		71	1	Dec-01	
							MERCANTIL SP		20	3	Dec-01	
							BBVA		15	4	Mar-03	
								EXCEL Econômico	28	4	Jun-98	
								Argentaria -Exteribank	116	4	Mar-00	
							ZOGBI (Finasa)		60	3	Dec-03	
								CREDITO SP	66	3	Dec-99	
							BEM		62	1	Dec-03	
							BEC		39	1	Dec-05	
							INTER AMEX		46	4	Mar-06	
								SRL	72	5	Dec-97	
							BMC		44	3	Oct-07	
							IBIBANK		37	4	Nov-09	
BRASCAN	Dec 95 - Sep 12	BRAS	Mellon Brascan	88	3	C						
BRB	Dec 95 - Sep 12	BRB	Banco de Brasília	32	1	C						
BTG PACTUAL	Dec 95 - Sep 12	UBSP	PACTUAL	9	2	C	UBS PACTUAL		13	4	Dec-09	*
								UBS WARBURG	45	4	Sep-06	
								OMEGA	74	3	Jun-98	
BTMUB	Dec 95 - Sep 12	BTMU	Banco de Tokyo-Mitsubishi Brasi	40	3	I						
BVA	Dec 95 - Sep 12	BVA		34	2	I						*
CEDULA	Dec 95 - Sep 12	CEDU		79	2	I						
CEF	Dec 95 - Sep 12	CEF	Caixa Econômica Federal	4	1	I						
CITIBANK	Dec 95 - Sep 12	CITI		10	3	C						
CR2	Dec 05 - Sep 12	CR2		93	2	I						
CREDIBEL	Dec 95 - Sep 12	CBEL		97	2	C						
CREDIT AGRICOLE	Dec 95 - Sep 12	CAGR		53	3	C	Crédit Lyonnais Brasil		65	4	Mar-07	*
								AGF BRASEG	58	4	Jun-01	

Brazil 1995-2012: banks included in the initial sample (III)

Source: the author from Banco Central do Brasil / *Evolução do SFN/ Anexos* (site www.bcb.gov.br), Nakane and Weintraub (2005), Makler (2000), Ness (2000)

Ownership: 1 = public or state bank; 2 = private domestic bank; 3 = foreign bank

(1) Information as for September 2012

Name of the bank or conglomerate (III) included in the initial sample	Observation period	Abbreviated name	Other usual denominations	Rank according to assets size (1)	Capital ownership (1)	Independent or Conglomerate (1)	Banks (II) under the control of the bank (III)	Banks (I) previously under the control of bank (II)	Rank according to assets size (1)	Capital ownership (1)	Date of transfer of control
CREDIT SUISSE	Dec 95 - Sep 12	CSUI	CSFB Garantia	12	3	C	GARANTIA		51	3	Jun-97
CRUZEIRO DO SUL	Dec 95 - Jun 12	CRUZ	CRUZEIRO	28	2	C					
DAYCOVAL	Dec 95 - Sep 12	DAYC		25	2	I					
DEUTSCHE BANK	Dec 95 - Sep 12	DEUT	DEUTSCHE	13	3	C					
DRESDNER	Dec 95 - Sep 12	DERS	DEUTSCH-SÜDAMERIKANISCHE BANK	68	3	I					*
FATOR	Dec 95 - Sep 12	FATR		60	2	C					
FIBRA	Dec 95 - Sep 12	FIBR		28	2	C					
FICSA	Dec 95 - Sep 12	FICS		67	2	C					
GERADOR	Sep 11 - Sep 12	GERA		75	2	I					
GERDAU	Dec 95 - Dec 09	GERD		100	3	C					
GUANABARA	Dec 95 - Sep 12	GUAN		64	2	I					
HSBC	Dec 95 - Sep 12	HSBC		6	3	C	BAMERINDUS LLOYDS		13 21	3 4	Dec-97 Sep-03
INDUSTRIAL	Dec 95 - Sep 12	INTL	Banco Industrial do Brasil	50	2	C					
INDUSVAL	Déc 00 - Juin 07	IVAL		41	2	C					
ING	Dec 95 - Sep 12	ING	Nederlanden	46	3	C					
INTERCAP	Dec 95 - Sep 12	ICAP		65	2	C					
INTERMEDIUM	Sep 08 - Sep 12	IMED		62	2	I					
ITAU	Dec 95 - Sep 12	ITAU		1	2	C	Banco Francês e Brasileiro (BFB) BANERJ BEMGE Banco do Estado do Paraná (BANESTADO) Banco do Estado de Goiás (BEG) BBA-CREDITANSTALT BANKBOSTON BOSTON NA UNIBANCO		25 12 34 21 46 13 13 91 6	4 2 2 2 3 5 4 4 5	Dec-95 Jun-96 Jun-98 Sep-00 Dec-01 Sep-02 Jun-06 Oct-08 Nov-08
								DIBENS CREDIBANCO BANDEIRANTES FININVEST INVESTCRED Banca Nazionale di Lavoro	44 45 22 47 71 44	3 5 4 5 5 4	Dec-97 Mar-00 Sep-00 Dec-00 Sep-02 Mar-04

Brazil 1995-2012: banks included in the initial sample (IV)

Source: the author from Banco Central do Brasil / *Evolução do SFN/ Anexos* (site www.bcb.gov.br), Nakane and Weintraub (2005), Makler (2000), Ness (2000)

Ownership: 1 = public or state bank; 2 = private domestic bank; 3 = foreign bank

(1) Information as for September 2012

Name of the bank or conglomerate (III) included in the initial sample	Observation period	Abbreviated name	Other usual denominations	Rank according to assets size (1)	Capital ownership (1)	Independent or Conglomerate (1)	Banks (II) under the control of the bank (III)	Banks (I) previously under the control of bank (II)	Rank according to assets size (1)	Capital ownership (1)	Date of transfer of control
JMALUCELLI	Dec 95 - Sep 12	PARA	PARANA	42	2	C					
JOHN DEERE	Dec 95 - Sep 12	JOHN		47	3	C	AGROINVEST		86	4	Dec-99
JP MORGAN CHASE	Dec 95 - Sep 12	JPMC		15	3	C					*
KDB BRASIL	Jun 06 - Sep 12	KDB		66	3	I					
KEB	Jun 01 - Sep 12	KEB		72	3	I					
LA PROVINCIA	Dec 95 - Sep 12	LAPR		81	3	I					
LA REPUBLICA	Dec 95 - Sep 12	LARE		95	3	I					
LUSO BRASILEIRO	Dec 95 - Sep 12	LUBR		70	2	I					
MÁXIMA	Mar 01 - Sep 12	MAXI	Banco Multi Stock	71	2	C					
MERRILL LYNCH	Mar 11 - Sep 12	MERR		33	3	C					
MODAL	Jun 96 - Sep 12	MODA		61	2	I					
MORADA	Dec 95 - Mar 11	MORA		67	3	I					
NATIXIS	Sep 08 - Sep 12	NATI		91	3	I					
ORIGINAL	Dec 95 - Sep 12	MATO	MATONE	43	2	C	FICRISA AXELRUD		111	3	Sep-02
PANAMERICANO	Dec 95 - Sep 12	PANA	Banco SS	19	2	C					
PECUNIA	Dec 95 - Mar 07	PECU		79	3	C					
PETRA	Mar 10 - Sep 12	PETR		98	2	C					
PINE	Dec 96 - Sep 12	PINE		30	2	C					
POTENCIAL	Sept 00 - Juin 07	POTT		90	2	I					
PROSPER	Dec 95 - Jun 12	PROS		72	2	C					
RABOBANK	Jun 96 - Sep 12	RABO		26	3	I					
RANDON	Sep 10 - Sep 12	RAND		85	2	I					
RENDIMENTO	Mar 01 - Sep 12	REND		57	2	C					
RENNER	Dec 95 - Sep 12	RENN		69	2	I					
RIBEIRAO PRETO	Dec 95 - Sep 12	RIBE		76	2	I					
RODOBENS	Sep 11 - Sep 12	RODO		55	2	C					
RURAL	Dec 95 - Sep 12	RURA		39	2	C					
SAFRA	Dec 95 - Sep 12	SAFR		8	2	C					

Brazil 1995-2012: banks included in the initial sample (V)

Source: the author from Banco Central do Brasil / *Evolução do SFN/ Anexos* (site www.bcb.gov.br), Nakane and Weintraub (2005), Makler (2000), Ness (2000)

Ownership: 1 = public or state bank; 2 = private domestic bank; 3 = foreign bank

(1) Information as for September 2012

Name of the bank or conglomerate (III) included in the initial sample	Observation period	Abbreviated name	Other usual denominations	Rank according to assets size (1)	Capital ownership (1)	Independent or Conglomerate (1)	Banks (II) under the control of the bank (III)	Banks (I) previously under the control of bank (II)	Rank according to assets size (1)	Capital ownership (1)	Date of transfer of control
SANTANDER	Dec 95 - Sep 12	SANT	Banco de Santander - BANESPA	5	3	C	GERAL DO COMERCIO		46	3	Jun-97
							BOZANO,SIMONSEN		26	5	Dec-97
							MERIDIONAL		23	4	Jun-00
							Banco do Estado de São Paulo (BANESPA)		6	4	Dec-00
							ABN AMRO		5	4	Jun-08
								BANDEPE	55	4	Dec-08
								REAL	7	3	Dec-08
								Banco do Estado de Paraib:	83	2	Sep-01
								SUDAMERIS	14	4	Sep-03
								AMERICA DO SUL	29	5	Jun-98
SMBC	Dec 95 - Sep 12	SMBC	Sumitomo Mitsui Banking, SUMITBANK	51	3	I					
SOCIETE GENERALE	Dec 95 - Sep 12	SOCG		17	3	C	Banco SOGERAL		60	5	Jun-99
							CACIQUE		58	3	Feb-08
SOCOPA	Sept 01 - Juin 07	SOCO	Soiedade Corretora Paulista	59	2	C					
SOFISA	Dec 95 - Sep 12	SOFI		38	2	C					
TRIANGULO	Dec 95 - Sep 12	TRIA		56	2	I					
VOTORANTIM	Dec 95 - Sep 12	VOTO		7	2	C					
VR	Dec 95 - Sep 12	VR		77	2	C					
WESTERN UNION	Sep 11 - Sep 12	WEUN		97	3	C					
WESTLB	Dec 95 - Sep 12	WEST	Westdeutsche Landesbank Girozentrale	52	3	C	BEAL		31	4	Mar-02

(*) Notes:

ABN AMRO	Securities ceded by the government to recapitalize PARAIBAN were not included in ABN AMRO financial statements
BESC	Former state bank transferred to the Federal Government in September 2000
BNB	Federal development bank
BNP PARIBAS	The share of BNL taken over by BNP since July 2006 was left in BNL financial statements, then consolidated with Unibanco from 2004 on
BVA	This bank takes in charge some types of credit on behalf of BNDES
CREDIT AGRICOLE	The balance-sheet of this conglomerate was split in our sample: the part AGF went to ITAU, and the part Crédit Lyonnais Brasil went to Crédit Agricole
DRESDNER	For December 1996 the financial statements of DEUTSCH and DBLABM were consolidated
HSBC	Taken over by HSBC Latin America Holdings (U.K.), the noncommercial branch Lloyds TSB S.A. (December 2003-June 2005) was not included in our sample
SANTANDER	Branch Santander de Negócios (BANSANDER), liquidated in 1997, was not included Branch Santander HISPANO, with no credit portfolio, ended its operations in May 2000 and was not included in our sample
UBS PACTUAL	UBS is an investment bank: the outstanding amount of credit of the conglomerate was essentially provided by Banco Pactual
UNIBANCO	The financial statements of BNL were fully consolidated with Unibanco, since information on the part transferred to BNP in July 2006 was not available
WESTLB	This bank was fully formed from assets of Banco Europeu para a América Latina (BEAL)

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