Credit shocks and monetary policy in Brazil: A structural FAVAR approach

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Abstract

This paper investigates the implications of the credit channel of the monetary policy transmission mechanism in the case of Brazil, using a structural FAVAR (SFAVAR) approach. The term “structural” comes from the estimation strategy, which generates factors that have a clear economic interpretation. The results show that unexpected shocks in the proxies for the external finance premium and the bank balance sheet channel produce large and persistent fluctuations in inflation and economic activity – accounting for more than 30% of the error forecast variance of the latter in a three-year horizon. The central bank seems to incorporate developments in credit markets – especially variations in credit spreads – into its reaction function, as impulse-response exercises show the Selic rate is declining in response to wider credit spreads and a contraction in the volume of new loans. Counterfactual simulations also demonstrate that the credit channel amplified the economic contraction in Brazil during the acute phase of the global financial crisis in the last quarter of 2008, thus gave an important impulse to the recovery period that followed.

Key Words: Structural FAVAR; Monetary Policy; Credit Channel
JEL Codes: E5; C55; C38

1 Introduction

The severe recession that followed the collapse of Lehman Brothers in September 2008 renewed the interest of academic professionals and policymakers in properly understanding the linkages between the financial sector and the real economy. A number of recent analyses have started to focus on the role played by financial intermediation as a channel to monetary policy. These studies find that disturbances originating in the credit sector played an

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important destabilizing role on the economic activity in the U.S. and other major nations during the great financial crises.

Recent empirical studies by Boivin, Giannoni and Stevanovic (2013), Gilchrist and Zakrajsek (2012), and Gilchrist, Yankov and Zakrajsek (2009) have found that credit shocks reinforced the downturn of the business cycle in the U.S. during the 2007-2009 crisis. Helbling, Huidrom, Kose and Otrok (2010) showed that these shocks were influential in driving the great global recession, while Ahmadi (2009) found, through a model with time-varying parameters, that credit spread shocks have a much stronger macroeconomic effect in the U.S. during recessions than in normal times.

In this work, we try to shed some light on the credit sector’s role in the business cycle in Brazil through a Structural Factor Augmented Vector Autoregressive model (SFAVAR). The structural nature comes from the fact that the estimation strategy generates principal components that have a clear economic interpretation. To assess the transmission of the credit shocks to the economy, we generate impulse response functions and carry out a variance decomposition analysis. In addition, we obtain counterfactual simulations in order to quantify the contribution of these shocks to the dynamics of the economic activity, inflation and monetary policy pursued by the central bank.

The choice of the FAVAR approach comes from the informational benefits provided by factor analysis. First, it permits the researcher to benefit from all of the information available in large datasets, overcoming the limitations imposed by the small degrees of freedom in standard VAR analysis. Second, this approach dispenses the necessity of arbitrarily choosing a specific variable to represent an economic concept. Third, since the factors rely on common components, it mitigates the problems related to the identification of shocks caused by the idiosyncratic element of individual series.

To the best of our knowledge, this is the first study using the FAVAR approach to explore the credit channel of the monetary policy transmission mechanism for the Brazilian case. Our results show that unexpected shocks in the proxies for the external finance premium and bank balance sheet channel produce large and persistent fluctuations in inflation and economic activity. In addition, the central bank incorporates developments in credit markets – especially variations in credit spreads – into its reaction function, as impulse-response exercises show the Selic rate is declining in response to wider credit spreads and a contraction in the volume of new loans. Counterfactual simulations also demonstrate that the credit channel amplified the economic contraction in Brazil during the acute phase of the global financial crisis in the last quarter of 2008, and thus gave an important impulse to the recovery period that followed. Although we identify the transmission of shocks originating in global financial markets on domestic financial conditions, they explain only a small fraction of the error forecast variance. This comes in opposition to the robust evidence of a large global contagion in the latest financial crisis, as well as signs of a liquidity spillover from the ultra-expansionary monetary policy pursued by the G4- central banks to emerging markets.

The paper is organized as follows: in the next section, we make a brief survey of the
theoretical and empirical research on the credit channel of monetary policy. We also present some stylized facts about monetary policy. Section 3 presents the SFAVAR approach and discusses estimation and identification issues. The dataset is presented in Section 4. Section 5 exhibits the main results of our unique analysis. Section 6 concludes.

2 The credit channel of monetary policy

The canonical representation of the role played by the financial sector is the “Modigliani-Miller theorem” (Modigliani and Miller, 1958), according to which, under complete markets and a frictionless financial sector, financial intermediaries act just like a “veil”, in the sense that they don’t play a particular part in business cycles. Consumers base their spending decisions entirely on their permanent wealth, so that movements in interest rates and asset prices are only relevant to the extent that they alter a household’s financial wealth and the incentives for intertemporal consumption. At the same time, financial and credit market shocks can only influence investment decisions by changing firms’ risk-free costs of capital and, therefore, the market value of the capital stock relative to its replacement cost.

The theoretical link between credit and business cycles is provided by models that represent a departure from the assumption of a frictionless financial sector and incorporates some imperfection, due to moral hazard and/or asymmetric information. The first channel through which financial sector disturbances can have persistent effects is the bank lending channel or “narrow credit channel” (Bernanke, 1983). This refers to the health of financial intermediaries and the consequent impact on its ability to extend credit. A central function of banks is to screen and monitor borrowers, which mitigates, at least in part, information and incentives problems. A monetary tightening or other shock that depletes banks reserves might force poorly capitalized institutions to pull back their credit lines in order to restore their capital positions. As a result, banks are prevented from making use of their “information capital”, which will lead to bank-dependent firms and households that don’t have alternative sources of finance to contract spending. Ultimately, this will deepen the real effects of the initial shock.

The other propagating mechanism of credit shocks extensively exploited in the literature is the “broad credit channel”, which operates through the creditworthiness of borrowers. Because creditors know that borrowers have an incentive to default when they have little equity attached to externally financed projects, they require collateral to reduce the lender’s risk, and/or demand a higher premium to provide external funds. Thus, there is an “external finance premium” relative to the internal financing generated by cash flows owed to the incentive problem.

Moreover, the “external finance premium” is inversely dependent on the borrower’s financial health. According to Bernanke (2007), this “creates a channel through which otherwise short-lived economic shocks may have long-lasting effects.” This propagating mechanism was dubbed a “financial accelerator” and can be applied to any disturbance –
including a monetary policy shock – that affects the borrowers’ financial health. Bernanke and Gertler (1989), Kyotaki and Moore (1997), Bernanke, Gertler and Gilchrist (1999), Carlstrom and Fuerst (2001), Iacovello (2005) are among the main works exploiting the external finance premium channel.\footnote{The information problem was behind Fisher’s (1933) description of the debt-deflation characterization of the 1930s crisis}

More recently, the broad credit channel has been formally modeled in a general equilibrium framework. Gilchrist, Ortiz and Zakrajsek (2009) introduced the Bernanke, Gertler and Gilchrist (1999) financial accelerator mechanism into Smets and Wouters’s (2007) DSGE model to capture linkages between credit conditions and the real economy. These authors present two different sources of disturbance: a supply shock affecting the external finance premium, and a demand shock, affecting the balance sheet of the firm. Gertler and Kiyotaki (2010), Cúrdia and Woodford (2010) and Gertler and Karadi (2011) also incorporated financial frictions into standard New-Keynesian models.

Financial intermediation has changed profoundly over the past three decades as capital markets have become more deeply liquid and accessible to non-depositary lenders. Therefore, banks no longer rely exclusively on deposits as a source of funding. They can issue debt on capital markets, or sell their portfolio of loans to brokers (dealers) or originate-to-distribute businesses. Nevertheless, the rise of non-bank lending doesn’t change the nature of the bank lending channel. In fact, non-deposit sources of capital are generally more expensive than deposits, reflecting the creditworthiness of the institution. This is a channel that is almost identical to the external finance premium discussed above, but instead of being related to the financial health of borrowers, it reflects the lender’s soundness. Therefore, this higher cost of banks’ funding will be passed on to borrowers, and it will amplify monetary and real shocks. At the same time, nonbank lenders will also face an external finance premium, as they need to raise funds in the capital markets to finance their operations at a cost that will depend on their financial strength.

Bernanke (2007) argued that the bank lending channel and the financial accelerator “can be integrated into the same logical framework”. In both cases, the balance sheet conditions are the channel through which financial shocks can be amplified and perpetuated, but while the former focuses on the borrower’s financial health, the latter transmission occurs through a lender’s balance sheet position.

### 3 Econometric strategy: The FAVAR approach

In order to access the credit channel of the monetary policy in Brazil, the econometric methodology applied in this analysis is the SFAVAR – a structural version of the Factor Augmented Vector Autoregressive, originally proposed by Bernanke, Boivin, and Eliasz (2005) – henceforth BBE.
Since the pioneering contributions of Sims (1992), the VAR methodology has been one of the leading tools in empirical works on monetary policy among central bankers and academics, either for forecasting purposes or for model validation. One of the technique’s best attributes is that it generates impulse-response dynamics that fit what one would expect from theoretical models, relying on simple and plausible identification schemes for the recognition of monetary policy innovations.

However, that doesn’t mean the methodology is immune to drawbacks. There are well-documented issues related to the impacts of different identification strategies on the outcomes of impulse-response functions. These can differ substantially depending on the identification hypothesis used by the researcher. Additionally, the VAR approach only accounts for the non-anticipated innovations, not the systemic effect of the monetary policy on the economy.

More recently, the literature has been paying closer attention to problems related to low informational content in standard VAR analysis. In fact, due to limitations imposed by the necessity of the system to conserve degrees of freedom, the methodology is not a fair representation of all the information set covered by central banks.

BBE presented two kinds of problems arising from low information content. The first issue is related to potential measurement errors of innovations in impulse-response analysis. As long as there is relevant information considered by the policymakers’ decision-making processes that is ignored in the VAR information set, the appropriate identification of the “shocks” can be undermined – for instance, the model might be treating a missed variable movement as a monetary policy shock, and vice-versa.

A classic example of this is the “price puzzle”, according to which monetary policy tightening is followed by a rise in inflation – an outcome totally at odds with conventional monetary policy theory. According to Sims (1992), this apparent “puzzle” has to do with the inadequate treatment of information held by the central bank regarding the future path of inflation. In other words, if the monetary authority acts preemptively to deviations of inflation from the target, and if it has some information that prices might increase in the future that are not contemplated by the VAR model, then the central bank action will be inadequately interpreted in the VAR as a “policy shock” rather than just the policymakers’ preemptive reaction to signs of deterioration in regards to future inflation. Since it is well established that there is a lag in monetary policy effects, the rise in policy rates is not able to completely offset the anticipated upward pressures in prices. This explains the apparent “price puzzle”.

The second problem arising from traditional VARs is that impulse-response functions can only be studied for those variables included in the model, which can impose an important limitation for policy purposes, as central banks usually monitor a large set of economic and financial variables. As BBE explained, no single series can be a perfect representation

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2 According to Bernanke and Boivin (2003), the central banks span hundreds of economic and financial series.
of an economic concept, so it is a matter of interest for policymakers to access the effects of monetary policy shocks not only on a specific series like industrial production or businesses’ capital expenditures, but also on other variables that can be equally representative of the concept of “economic activity”, such as personal income, retail sales, or construction spending.

In order to overcome these limitations, BBE introduced the FAVAR (Factor Augmented Vector Autoregressive) methodology, which complements the traditional VAR approach with factor analysis techniques, making it possible to summarize the information contained in a large dataset in a small number of “latent” factors. By “augmenting” the VAR with “factors” containing relevant information about the state of the economy, the FAVAR methodology offers a way to deal with the limitation of degrees of freedom usually present in traditional VAR models. This technique is also a practical tool for central banks to evaluate the effect of monetary policy and real shocks on a broad set of economic and financial series, as opposed to assessing only a handful of variables contained in the VAR.

3.1 Credit Channel in FAVAR models

Some works use the FAVAR methodology proposed by BBE to assess the empirical role of the credit channel of monetary policy. Gilchrist, Yankov, and Zarajsek (2009) constructed a broad array of credit spread measures from secondary bond prices and used them to generate impulse-response functions from a structural FAVAR. The results confirmed that unexpected increases in the credit spread cause a large and persistent contraction of the economic activity in U.S., accounting for more than 30% of the error forecast variance in a two-year horizon.

In a very large dataset environment, Boivin, Giannoni, and Stevanovic (2013) estimated a structural factor model for the U.S. economy using the contemporaneous timing restrictions procedure proposed in Stock and Watson (2005) to identify the structural shocks. The results showed that an idiosyncratic deterioration in credit markets has important effects on real activity measures, inflation, leading indicators and credit spreads.

Helbling et al. (2010) obtained the first principal component in various macroeconomic and financial variables for the G-7 countries to evaluate the role of credit in VAR models. They found that credit shocks originating in the U.S. were influential in driving global activity during the latest global financial crisis.

Some works rely on time-varying parameter models to assess changes in the credit transmission over time. In a time-varying FAVAR, Eickmeier, Lemke and Marcellino (2011) showed that U.S. financial shocks have a considerable impact on growth in other advanced economies, with the transmission gradually increasing since the 1980s. Consistent with common sense, they found the largest impact in the sample occurring during the 2008 crisis.

Ahmadi (2009) estimated a Bayesian FAVAR with time-varying parameters and volatilities for a U.S. dataset spanning the period of 1926-2009. Although not always the case, the
periods of high volatility in the common components of credit spreads often coincide with NBER dated recessions. During these periods, monetary policy and credit spread shocks have a much greater and more persistent effect on the macroeconomic variables than on average.

3.2 Econometric model

The original FAVAR model has the following structure:

Let $Y_t$ be a $M \times 1$ vector of observed economic variables and $F_t$ a $K \times 1$ ($K$ “small”) vector of non-observed factors which can represent generic economic concepts like “economic activity”, “inflation”, or “credit conditions”.

Now assume that $Y_t$ and $F_t$ have the following time series equation:

$$
\begin{bmatrix}
F_t \\
Y_t
\end{bmatrix} = \Phi(L) \begin{bmatrix}
F_{t-1} \\
Y_{t-1}
\end{bmatrix} + \nu_t
$$  \hfill (1)

Where $\Phi(L)$ is an order-$d$ polynomial that has the usual restrictions present in the VAR approach and $\nu_t$ is a zero-mean error with covariance matrix $Q$.

If the coefficients of $\Phi(L)$ in (1) that link $Y_t$ and $F_{t-1}$ are equal to zero, then the equation does not differ from a traditional VAR in $Y_t$; otherwise, the system expressed by (1) is a VAR in terms of $Y_t$ and $F_t$ – or, as BBE labeled it, a Factor-Augmented Vector Autoregression (FAVAR).

Since the vector $F_t$ is not observed, equation (1) cannot be estimated directly. However, once the factors represent “underlying” economic forecasts, factor model techniques allow them to be inferred indirectly through a dataset of an observed series. Let $X_t$ be a $N \times 1$ vector containing observed economic variables (usually called the “informational” series), with $N$ being “sufficiently large” (at least larger than the number of periods $T$, and much larger than the number of factors $K + M \ll N$). Now, BBE propose that the non-observed factors $F_t$ can be related to the informational series throughout the following observation equation:

$$
X_t = \Delta^f F_t + \Delta^y Y_t + \varepsilon_t
$$  \hfill (2)

Where $\Delta^f$ is a $N \times K$ loading matrix, $\Delta^y$ is a $N \times K$ matrix of coefficients, and $\varepsilon_t$ is a $N \times 1$ error vector with a zero mean.

According to equation (2), the series in $X_t$ can be interpreted as stochastic means of the factors contained in $F_t$ conditioned on $Y_t$ – which can also include lags in the fundamental factors. Because of that, Stock and Watson (2002) referred to this equation without the observed factors $Y_t$ as a “dynamic factor model”.

In the original specification of BBE, the vector of observed factors contains only the monetary policy instrument. However, the approach is flexible enough to allow the inclusion of other economic and financial variables in $Y_t$. 

7
3.3 Identification of the structural factors

The main contribution of the original \textit{FAVAR} model proposed by BBE, given by equations (1)-(2), is that one benefits from relevant information about the state of the economy that is covered in a large number of economic and financial series (a “data-rich” environment), through the inclusion of non-observed common factors within the \textit{VAR}.

However, these common factors are just pure statistical objects, with no sort of economic interpretation assigned to them. This might impose a serious impediment to the objective of this work – after all, the empirical assessment of the credit channel of monetary policy requires an unambiguous identification of the credit shocks. Of course, this cannot be done without some solution for the identification problem of non-observed factors.

To deal with such a limitation, this analysis follows the \textit{SFAVAR} (Structural \textit{FAVAR}) approach proposed by Belviso and Milani (2006), which goes one step ahead of the original formulation proposed by BBE by introducing a set of restrictions into the estimation procedure, so that it becomes possible to attribute an economic interpretation to the common factors.

Take a partition \(X^i_t\), \(X^i_t\), \(\cdots\), \(X^I_t\) of \(X_t\), where \(X^i_t\) is a \(N^i\times 1\) vector, \(I\) represents the number of different “economic concepts” present in the dataset, and \(\sum_{i=1}^I N^i = N\). Assume now that each \(X^i_t\) is explained exclusively by one “economic concept”. That is, there is a correspondent partition of the \(F_t\) vector given by \(F^1_t\), \(F^2_t\), \(\cdots\), \(F^I_t\), where \(F^i_t\) is such that it explains the dynamics of \(X^i_t\) exclusively, for all \(i\) (and conversely, \(X^i_t\) is uniquely explained by \(F^i_t\)). Then, we can rewrite the system of equations (1)-(2) in the following way:

\[
\begin{bmatrix}
F^1_t \\
F^2_t \\
\vdots \\
F^I_t \\
Y_t 
\end{bmatrix} = \Phi(L) \begin{bmatrix}
F^1_{t-1} \\
F^2_{t-1} \\
\vdots \\
F^I_{t-1} \\
Y_{t-1} 
\end{bmatrix} + \nu_t 
\]

(3)

\[
\begin{bmatrix}
X^1_t \\
X^2_t \\
\vdots \\
X^I_t 
\end{bmatrix} = \begin{bmatrix}
\Delta^I \\
0 \\
\vdots \\
0 
\end{bmatrix} \begin{bmatrix}
F^1_t \\
F^2_t \\
\vdots \\
F^I_t 
\end{bmatrix} + \varepsilon_t 
\]

(4)

Where \(E(\varepsilon^i_t \varepsilon^j_t) = 0\) for all \(i, j = 1, \cdots, I\) and \(i \neq j\).

With the set of restriction presented above, if one assumes that the vector of \(X_t\) is divided into subsets of variables that share the same “economic concept” – for example, a subset of economic activity, a subset of inflation, a subset of credit spreads, and so on – the common force that drives each subset of variables (the dynamic factor) now has an economic
interpretation. For example, the common factor estimated from the set of variables like industrial production, retail sales and unemployment rates might be interpreted as the “economic activity” factor. Likewise, an “inflation factor” is the common factor estimated from the set of variables containing consumer and wholesale price indexes.

Similar to the Belviso and Milani (2006) approach, in this paper, the vector $X_t$ was partitioned so that the informational variables are organized according to the following “economic concept”: economic activity; inflation; credit; domestic financial condition, global financial condition. As was mentioned in the previous section, only one factor $F_t$ explains each subset of $X_t$.

Now it is possible to identify the credit channel of monetary policy: it is the common factor derived from a set of variables related to a specific dimension of credit activity. In the present paper, two different credit factors were identified:

- **Credit Spread factor**: the inclusion of this factor aims to capture the effects of the external finance premium. In most cases, fluctuations in credit spreads are essentially caused by changes in the external finance premium, with demand factors playing a minor role. Therefore, credit spreads can be seen as good proxies for the external finance premium.

- **Credit Volume factor**: as was previously discussed, credit shocks can materialize not only through changes in the cost of credit (the external finance premium discussed above), but also through the amount of resources banks are willing or are able to lend, according to their risk-adjusted capital and liquidity bases – as we mentioned in Section 2, this is the bank lending channel. Therefore, the volume of credit can be understood as a proxy for the bank lending channel.

There are two reasons justifying the inclusion of the financial condition factors³. There are two reasons justifying the inclusion of the financial condition factors. The first is to control the VAR estimation for changes in those domestic and global financial variables that can influence the economy, such as exchange rates, term interest rates, commodity prices and stock prices. This is particularly important for monetary policy studies in Brazil, since, until recently, the country used to be frequently subjected to typical balance of payment type crises that prompted very large exchange rate depreciations. These issues led to significant inflationary pressures and forced monetary policy to react aggressively, producing sharp disruptions in economic activity.

The second reason is an attempt to quantify the effects on the Brazilian business cycle from liquidity spillovers caused by non-conventional monetary policies practiced in developed economies.

It is also worth noting that the set of restrictions applied for the identification of structural factors also helps to overcome the problem of measurement errors of an individual

³See Hatzius et al. (2010) for a discussion on financial conditions as a monetary policy channel.
economic series. In fact, through equation (4), the dynamics of each one of the variables belonging to a specific economic concept is solely determined by the common factor, with the exception of an idiosyncratic error, which might be interpreted as a measurement error and/or a real idiosyncratic shock. Since it is the factor – not the individual series – that enters equation (3), the dynamics of the economy are not distorted by idiosyncratic shocks that normally affect an individual time series.

3.4 Estimation of the \textit{SFAVAR} model

The \textit{SFAVAR} model comprehends the system of equations (3)-(4). BBE present two different estimation strategies that have become widely used in the \textit{FAVAR} literature.

The first procedure is a Bayesian estimation approach, according to which equations (3) and (4) are jointly estimated by the Gibbs sampling technique, developed by Geman and Geman (1984) and extended by Gelman and Rubin (1992) and Carter and Kohn (1994)\footnote{See Kim and Nelson (1999) for a survey.}. The second strategy, detailed below, is a two-step procedure based on Principal Component Analysis (\textit{PCA}).

Although the Bayesian estimator has the benefit of accounting for the structure of the transition equation in the estimation of the factors, in this work we only implement the \textit{PCA} methodology. Besides being computationally much more burdensome, the Bayesian approach doesn’t seem to have a meaningful or practical advantage. Indeed, Belviso and Milani (2006) showed that the two methods generate highly correlated and, sometimes, almost identical factors. BBE even determined some outcomes for the impulse-response functions in the Bayesian estimation that are at odds with economic theory and other empirical experiments, such as the liquidity and price puzzles.\footnote{According to BBE, these puzzles might be a problem of the inadequate identification of policy shocks by the Bayesian approach.}

In the first step, the estimated factors \((\hat{F}_1^1, \hat{F}_1^2, \cdots, \hat{F}_1^I)\) are the first principal components obtained from each group of a series that forms an economic concept. Once the factors are obtained, in step 2 they are used within the \textit{VAR} represented by equation (3) to estimate \(\Phi(L)\).

4 Dataset

This paper used a monthly balanced panel for the period spanning from January 2003 to March 2012, containing 288 series relative to the following economic concepts: Economic Activity; Inflation; Credit; Domestic Financial Conditions; and Global Financial Conditions. For the credit series in particular, 39 series were selected that related to the spread on new loans (17) and the volume of new loans (22 series).
The domestic financial conditions dataset contains bilateral exchange rates of the Brazilian real; the term structure of the local interest rate curve for various maturities, the five-year credit default swap, Brazilian stock market index (Ibovespa), capital account flows, money aggregates and local capital markets activity.

Because they are expectational series, they share a very high degree of colinearity with other factors – especially the monetary policy rate. Therefore, in order to capture only the information provided by the Domestic Financial factor that is orthogonal to the rest of the information set, we added to the specification of the SFAVAR only the residuals of the Domestic Financial factor regression in the other economic factors.

Among the series included in the global financial conditions dataset is the G-4 policy rate and the term structure for various maturities; the S&P index; the VIX index; and the USD basket index (DXY index). To capture the liquidity effects posed by the expansionary balance sheet policies of the G-4 central banks, we followed the solutions proposed by the IMF (2010a, 2010b) and Psalida and Sun (2011), and included the total assets held by the Federal Reserve Bank, the European Central Bank and the Bank of England in the dataset.\(^6\)

ADF unity root tests were applied, and the series were transformed to ensure stationarity when appropriate. The nominal data were deflated by the IPCA, Brazil’s consumer price index.\(^7\)

An important practical difference present in this work, in relation to other empirical studies about the monetary policy channel in Brazil, has to do with the treatment of the monetary policy instrument – in particular, the issue of the unit root which is present in the Selic time series. As Bevilaqua, Minella and Mesquita (2007) argued, the consistent achievement of inflation targets in past years, the declining trend of public debt and the reduction of external vulnerability contributed to a sizeable compression of the uncertainty premium in Brazilian financial assets. This opened the door for a consistent reduction of the Selic rate over the past decade.

From a purely statistical point of view, one could treat this phenomenon merely as a unit root process and, therefore, proceed with the usual differentiation to assure stationarity. However, by doing so, the researcher would be ignoring the effects of the profound transformations that took place in the Brazilian economy over the past years that prompted the consistent decline in interest rates. The researcher would then be mistakenly labeling the movement of those rates as just a cyclical phenomenon rather than a structural change in the neutral interest rates.

This is particularly relevant in the present context because of the necessity to identify monetary policy shocks. As it is well established in New-Keynesian models, movements in the neutral rates per se do not produce any effect on inflation or economic activity. Rather,\(^6\)

Although the Bank of Japan has also been undertaking asset purchases, there isn’t a time series on a monthly basis for the period covered in this study.

\(^7\) The detailed description of the series and the transformations applied in each series can be provided by the authors upon request.
only deviations of the actual interest rates from their neutral level are prone to engineer business cycles. Therefore, it is necessary to control for neutral rate movements in order to properly identify genuine policy shocks.

Since the neutral interest rate is not an observed variable, it is necessary to rely on some procedure to differentiate changes in the actual interest rate from deviations of the interest rate in relation to its equilibrium level. To address this point, the Hodrick-Prescott filter\(^8\) was used, with the obtained cyclical component being a proxy for the interest rate deviation. This was the monetary policy variable included in the FAVAR. Such an approach was applied not only to the monetary policy instrument (the Selic rate), but also to other interest rates for Brazil and other countries included in the data set.

We followed a similar approach in the case of data for new loans. Beyond the decline of the interest rate, macroeconomic stability in Brazil opened the door for a credit boom. Therefore, after decades of economic stagnation that led to very low levels of financial intermediation – in the beginning of the 2000s, credit activity in Brazil lagged behind most of the other nations with emerging markets – the fast growth of credit over the recent years should not just be associated with a cyclical, mean-returning process. Instead, a relevant portion of this movement can be understood as a structural change, which allowed the country to move from a former equilibrium of low credit penetration to a new steady state more compatible with current macroeconomic fundamentals. In order to isolate the structural phenomenon, the credit stock data used in this work is the cyclical component obtained from the Hodrick-Prescott filter.

5 Empirical evidence on the role of the credit channel in Brazil

Figure 1 shows the estimated factors. In the months before the acute phase of the global crisis, the activity and inflation factors presented high rates of growth, boosted by strong credit activity, as can be noticed by the very positive values for the Credit Volume factor and very low credit spreads. Because the central bank was tightening the Selic rate, the yield curve was very steep, which explains the very high levels of the Domestic Financial factor.

With the economic and financial mayhem that followed the collapse of Lehman Brothers, economic activity and inflation plunged. The Credit Spread factor skyrocketed, which is explained by the sharp rise in the external finance premium. The global liquidity crunch and banks’ concerns with their liquidity and capital positions led to a deep contraction of the Credit Volume factor.

\(^8\)The “smoothing parameter” \(\lambda\) was calibrated with “power rule” of 4, as is suggested by Ravn and Uhlig (2002)
As was mentioned previously, the aggressive policy reaction domestically and abroad prompted a V-shaped recovery in some emerging nations. This was the case for Brazil. By the second quarter of 2009, the Economic Activity factor was back in positive territory, inflation was creeping up again, and credit spreads were once again very tight. Because of the collateral damage of the market’s disruptions on financial intermediation, the growth of credit took a little longer to normalize. This explains why the Credit Volume factor only returned to showing positive rates of growth in the beginning of 2010.

Not surprisingly, since early 2005 global financial conditions were becoming tighter as central banks in most advanced economies were scaling up interest rates as an attempt to tame inflationary pressures and unwind the housing bubble – this explains the very positive levels for the Global Financial factor during this period. Obviously, this was totally reversed in the end of 2008 with monetary policy easing and other non-conventional responses that came into play after the Lehman’s debacle. Since then, the Global Financial factor has been in very expansionary (negative) territory most of the time, with the exception being the first half of 2011 – after the end of the second quantitative easing in the U.S. and before the Federal Reserve renewed balance sheet operations and reshaped its communication tools aimed at providing more stimulus to the economy.

5.1 Impulse response functions

Figures 1 – 3 present the impulse response functions. All graphs were constructed with an 80% probability band. In principle, the confidence bands should take into account the effect of generated regressors. However, since the dataset in the present work is relatively large, we did rely on the result of Bai and Ng (2006) which shows that PCA estimators are $\sqrt{T}$ consistent and asymptotically normal if $\frac{p}{T} \rightarrow 0$. In fact, using a much smaller dataset, Belviso and Milani’s (2006) results show that the uncertainty of the factors is almost totally neglectable.

Tests for lag exclusion suggested an SFAVAR with three lags. The innovations in the system were identified by means of Cholesky decomposition, with the following ordering: Economic Activity factor; Inflation factor; the Selic rate; Credit Spread factor; Credit Volume factor; Domestic Financial factor; and Global Financial factor.

The reasoning behind the choice of ordering the Selic rate after the Economic Activity and Inflation factors is that the monetary authority is able to monitor the current state of the economy, but the effects of policy innovation take place only with a lag. The idea of ordering the credit and financial factors last is derived from the assumption that financial variables reflect all the current information available, but do not contain additional information besides that which is directly observed by the policymakers.
5.1.1 Monetary Policy Shock

Figure 2 presents the response to an unexpected one-standard deviation of the Selic rate. The dynamics of the system follow what is expected from the theory: a contractionary monetary policy shock generates a permanent decline in the Economic Activity factor, with the maximum effect taking place around 10 months after the initial disturbance.

The response of inflation does not show the price puzzle. Following a one-standard deviation shock to the policy rate, the Inflation factor presents the characteristic negative hump-shaped behavior present in sticky-prices models, taking 14 months to reach its lowest level.

The policy shock simultaneously produces a jump in the Credit Spread factor and a decline in the Credit Volume factor. Such behavior is totally consistent to what is predicted by financial accelerator and bank lending channel theoretical models. The rise in uncertainty about the credit quality of firms and households makes financial institutions more conservative about expanding their portfolio of loans. This translates into both higher spreads and tighter standards. At the same time, the rise of the Selic rate decreases financial institutions’ liquidity and capital buffers – in other words, it raises the external finance premium of banks – dampening their ability to lend. The expected outcome is a decline in the amount of new loans, represented by the Credit Volume factor.

Although not statistically significant, the Selic increase produces a decline in the Domestic Financial factor. A possible explanation for this is the nominal exchange rate appreciation and the yield curve flatterning that are normally associated with contractionary monetary policy episodes.

5.1.2 Credit Spread Shock

Figure 3 shows the cumulative responses to a one-standard deviation widening in the Credit Spread factor. As was expected, the Economic Activity and Inflation factors contract. It is worth noting that the impact of the Credit Spread shock is more frontloaded than the Selic shock, reaching a maximum effect in eight months.

It is also interesting to mention the response of the monetary policy: to mitigate the contractionary effects of the rise in the Credit Spread factor, there is a statistically significant decline in the Selic rate. This suggests that the Brazilian Central Bank’s reaction function responded to developments in credit spreads.

5.1.3 Credit Volume Shock

A positive innovation to the Credit Volume factor (Figure 4) generates an expansion of the Economic Activity factor and an increase in the Inflation factor. Although not statistically significant, the Selic rate rises to counteract the expansionary effects of the shock in the volume of credit.
5.1.4 Financial Conditions Shock

Figure 5 shows that a rise in the Domestic Financial factor—understood as a contractionary innovation, according to the estimated factor loadings—produces a response in the system’s economic variables that align with what is predicted: economic activity and inflation fall, the Credit Spread factor widens, while the Credit Volume factor contracts.

Even more interesting is the reaction of the monetary policy, as the Selic rates increase. This seems to be counterintuitive, as one would normally expect an expansionary policy reaction in response to a contractionary shock. Such an apparent contradiction might be explained by a misspecification problem.

A closer look to the stylized facts during the period spanned in this study again reveals an important detail: due to the financial disruptions following the Lehman Brothers’ failure, in January 2008 the central bank reversed course in the tightening process and initiated an aggressive monetary policy easing that totaled 500 basis points (bp). This dismantled the substantial hikes implied in the yield curve—meaning a substantial easing in domestic financial conditions and, therefore, a decline in the Domestic Financial factor. Thus, it is possible that some sort of misspecification problem might be mistakenly steering us to the conclusion that a contractionary shock in the Domestic Financial factor leads to a contractionary monetary policy response—when the actual causality probably runs reversely.

Figure 6 portrays the system’s response to a contractionary shock in the Global Financial factor. Almost all variable reactions are not statistically significant, with the only exception being the Domestic Financial factor, which shows an expected contraction.

5.2 Variance decomposition

Besides the impulse response exercise, another experiment normally used in monetary policy analysis is variance decomposition. This test determines the fraction of the system’s variables error forecast variance at a given horizon that can be attributed to a specific shock.

Table 1 presents the system’s variance decomposition for a 36-month horizon. It should be noted that the credit shocks are extremely important for the Economic Activity factor: the Credit Spread factor posts the largest individual contribution—more than 17%—and combined with the Credit Volume factor, they both explain almost 31% of the total error forecast variance of the Economic Activity factor. Another significant occurrence is that the financial factors together account for 17%. The monetary policy contribution is moderate, around 11%.

In the case of the error forecast variance of the Inflation factor, although the credit factors contribution is not that large—around 8%—the financial factors account for a meaningful portion: more than 20%. Interestingly, the Global Financial factor alone represents 13% of the total variance—the largest after the significant 15% contribution.
from monetary policy. In the case of monetary policy, the Credit Spread factor is the single most important source of variance – 25% of the total. Together with the Credit Volume factor, both credit factors explain more than 30% of the Selic variance. The combined financial factors also have a sizeable contribution, around 20%. It is particularly noticeable that the credit and financial factors respond to a much larger part of the monetary policy variance than the Economic Activity or Inflation factors – something that opposes the widespread consensus that the monetary authority follows some form of Taylor rule, with the output gap and inflation deviation being the only arguments. However, these facts can still be reconciled when one remembers that credit and financial factors are good leading indicators and the central bank reacts preemptively to present information that points to future deviations in the output gap and inflation.

As has become evident in the impulse-response analysis, monetary policy makes an important contribution to the Credit Spreads variance – approximately 15% of the total variance – although it is less relevant in the case of the Credit Volume factor, by explaining a little more than 5%.

Not surprisingly, the Domestic Financial factor plays an important role in credit factor dynamics, accounting for almost 12% of the Credit Spread factor variance – the second largest source of perturbation – and 13% of the Credit Volume – the largest individual contribution.

The Global Financial factor poses a modest contribution to the Domestic Financial factor – only 6.5% of the error forecast variance – which is somewhat disappointing when we are faced with the evidence of contagion during the financial crises, as well as liquidity spillover from the ultra-expansionary monetary policy pursued by the G-4 central banks in the past years. This could be reconciled if we assume the hypothesis that financial contagiousness is state-dependent\(^9\), and tends to be much higher in periods of severe market stress – when different asset classes’ correlations tend to degenerate and get close to one. If this explanation proceeds, models with time-varying parameters could show that the share of the Domestic Financial factor variance explained by the Global Financial factor might have been very significant during the great financial crises of 2008.

\textbf{5.3 Counterfactual Simulation}

How important were credit shocks in Brazil during the global financial turmoil of 2008? What were these shocks contribution to the fast recovery that Brazil enjoyed in the aftermath of the crises? How different could the monetary policy pursued by the Central Bank of Brazil have been in the absence of the kind of credit shocks that hit the economy in the past years? Given the relevance of the credit channel of the monetary policy transmission mechanism for the Brazilian case evidenced in the previous exercises, it would be helpful to investigate these questions.

\(^9\)Ribeiro and Veronesi (2002) is the classical reference.
To evaluate the role of credit during different periods of Brazil’s recent economic history, we followed Helbling et al. (2010) by performing a counterfactual exercise. In particular, we ran simulations where the idiosyncratic shocks of both credit factors were set as zero in the SFAVAR model, so that by comparing the counterfactual dynamics with the actual one, it becomes possible to gauge the idiosyncratic contribution of the credit activity to the Brazilian business cycle and the monetary policy pursued during different periods.

The simulations were performed for three different periods of Brazil’s recent history: the fast growing phase of the last decade until the global financial crisis (March 2003 to March 2009); the recovery phase in the aftermath of the crises (April 2009 to December 2010); and the adjustment period, following the recovery, when authorities introduced numerous measures to cool down an overheating credit market (January 2011 to March 2012). In each of these periods, the shocks to the Credit Spread and Credit Volume factors were set to zero. The cumulative dynamics for the simulated Economic Activity and Inflation factors, as well as the monetary policy trajectory, were then compared to the actual series.

Figure 7 shows that the counterfactual Economic Activity and Inflation factors closely follow the actual series during most of the first period. However, this changes dramatically after December 2008, when the economic activity suffers a blow from the general panic after Lehman Brothers’ bankruptcy: in March 2009, the actual Economic Activity factor reaches an accumulated level almost 5% below what would have been the case if the credit factors didn’t present the idiosyncratic shocks that were actually observed. In other words, the credit shocks during this period account for almost five percentage points (pp) of the decline in the Economic Activity factor. The simulated Inflation factor’s dynamics follow a similar pattern: in March 2009, the cumulated inflation is four pp lower due to the shocks in the Credit Spread and Credit Volume factors. This shows that the credit channel played a very large role in transmitting external financial issues to the Brazilian economy during the 2008 crisis. Not surprisingly, this had an important implication on monetary policy: the simulated Selic would have been set 125 bp higher in the absence of such large credit shocks.

Figure 8 shows that the credit shocks were also relevant for the economy’s dynamics during the recovery period that followed (April 2009 to December 2010). First, Figure 8 shows that the counterfactual series run above the actual one in 2009, which suggests that the credit channel was still somewhat repressing the economy in the initial phase of the recovery. This changes completely in the beginning of 2010, as the credit activity starts giving an extra push to the Economic Activity factor. At the end of 2010, the level of the actual series is almost 3% higher than it would have been in the absence of the idiosyncratic credit shocks. The results confirm that the strong policy response in the form of the credit expansion of public banks could have been a determinant in the fast rebound of the Brazilian economy in the aftermath of the crisis.

The Inflation factor follows an almost identical dynamic. Until the end of the first half of 2010, the actual Inflation factor is contained by the modest expansion of credit. Again, as the expansionary shocks in the Credit Spread and Credit Volume factors start to kick
in, the actual Inflation factor accelerates to the point that it finishes the year 1.70 pp above the counterfactual series. Obviously, the central bank had to conduct a tighter monetary policy due to the expansionary effects of credit: in the end of 2010, the Selic rate is almost 1.5% higher than otherwise, due to the idiosyncratic shocks in the credit factors.

We couldn’t identify a contribution of credit for the sharp deceleration in economic activity and inflation during the period of policy adjustment, starting from January 2011. This is at odds with what the stylized facts suggest, since we would expect that the macro-prudential measures aimed at taming the fast rate of credit expansion would have been a determinant for the subdued economic activity and inflation dynamics observed in this period. To the contrary, Figure 9 shows, if anything, that the idiosyncratic shocks in the Credit Spread and Credit Volume factors gave an extra push to activity and inflation.

6 Conclusion

The great financial crisis renewed the interest of academics and policymakers in better understanding the linkages between developments in the financial sector and the real side of the economy. In this analysis, we tried to investigate the empirical implications of the credit channel to monetary policy transmission in the case of Brazil.

By relying on principal component analysis, we obtained proxies for the external finance premium and the balance sheet channel. The estimation strategy of the FAVAR system allowed us to attach a clear economic interpretation to the factors and, therefore, to identify the structural shocks.

The results of impulse response functions and variance decomposition analysis evidenced that the credit shocks account for large and persistent fluctuations in activity and inflation in Brazil. For economic activity in particular, the shocks contribute to a much larger share of the error forecast variance than the monetary policy instrument itself – around 30%. Indeed, the central bank seems to incorporate functions developments in credit markets in its reaction, especially in regards to changes in credit spreads.

Our research also shows a contraction in the domestic financial conditions that produces the effects in credit activity in accordance to what is suggested by theoretical models: the rise in uncertainty increases the external finance premium, leading to wider credit spreads; at the same time, balance sheet and liquidity constraints pose as a contraction in the supply of loans, thus generating a decline in the volume of new loans.

Counterfactual simulations also demonstrate that the credit shocks were a determinant in amplifying the economic contraction in Brazil during the acute phase of the global financial crisis in the last quarter of 2008. These simulations also confirm that the fast credit expansion provided an important impulse to the recovery in 2010. This was behind the central bank’s decision to implement macroprudential measures to rein in the overheating credit activity.

Although we were able to identify the transmission of shocks originating in global
financial markets to domestic financial conditions, they only explain a small fraction of the error forecast variance. Furthermore, the shocks’ effects on the two credit factors seemed not to be statistically significant. This comes in opposition to the robust evidence of a large global contagion witnessed in the latest financial crisis, as well as signs of a liquidity spillover to emerging markets from the ultra-expansionary monetary policy pursued by the G-4 central banks in the past few years.

These outcomes deserve further analysis. Introducing the hypothesis of time-varying parameters to the SFAVAR estimation is one possible way to explore this scenario. This could be justified if one supposes that the influence of the global financial conditions on the domestic financial market is not independent from the state of the global economy and financial markets – relatively weak in normal times, but very significant in periods of global financial distress.

7 References


Figure 1: Estimated Factors
Figure 2. Cumulative impulse-response functions due to a 1 standard deviation shock of the Selic rate.

Note: The solid lines represent the mean and the dotted lines represent the 10th and 90th percentiles.
Figure 3. Cumulative impulse-response functions due to a 1 standard deviation shock of the Credit Spread Factor

Note: The solid lines represent the mean and the dotted lines represent the 10th and 90th percentiles.
Figure 4. Cumulative impulse-response functions due to a 1 standard deviation shock of the Credit Volume Factor

Note: The solid lines represent the mean and the dotted lines represent the 10th and 90th percentiles.
Figure 5. Cumulative impulse-response functions due to a 1 standard deviation shock of the Domestic Financial Factor

Note: The solid lines represent the mean and the dotted lines represent the 10th and 90th percentiles.
Figure 6. Cumulative impulse-response functions due to a 1 standard deviation shock of the Global Financial Factor

Note: The solid lines represent the mean and the dotted lines represent the 10th and 90th percentiles.
Table 1: *SFAVAR* - Variance Decomposition

<table>
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<tr>
<th>Variable of Interest</th>
<th>Monetary Policy</th>
<th>Credit Spread</th>
<th>Credit Volume</th>
<th>Domestic Financial</th>
<th>Global Financial</th>
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<td>Economic Activity Factor</td>
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<td>27.0%</td>
<td>38.5%</td>
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</tbody>
</table>
Figure 7. Counterfactual simulations for the period April 2003 to March 2009

Note: The solid lines represent the original series and the dotted lines represent the simulated series.
Figure 8. Counterfactual simulations for the period April 2009 to December 2010

Note: The solid lines represent the original series and the dotted lines represent the simulated series.
Figure 9. Counterfactual simulations for the period January 2011 to March 2012

Note: The solid lines represent the original series and the dotted lines represent the simulated series.