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Economic dynamics during periods of financial stress: Evidences from Brazil☆

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ABSTRACT

This paper investigates the differences in macroeconomic dynamics that occurred during instabilities in the Brazilian financial market from 2000 to 2015. In this regard, we introduced the Brazil Financial Stress Index as a proxy for financial stress, and investigated its interaction with real activity, inflation and monetary policy using a Markov-switching VAR model. We could verify distinct economic reactions during stressful periods. Furthermore, our results demonstrate that appropriate policies for some countries in normal times, such as an expansionary monetary policy, can worsen the scenario in an adverse situation, indicating that a government might deepen a financial crisis if policy-makers implements a policy used successfully during a regime that is economically and behaviorally dissimilar from tense states.

1. Introduction

During periods of international crisis, governments take measures to mitigate the effects of such crises on their national economy. These actions include fiscal incentives to ease monetary stimulus as well as interventions in the financial market and the exchange rate. The policies the governments adopt can prevent overflow of the international crisis into the local economy, if said policies are appropriate. However, since these changes are undertaken during periods of instability, fiscal and monetary policies may not have the expected effects.[1] Furthermore, as argued by Espinoza, Fornari, and Lombardi (2012), along with the global recession of 2007–2009, the instabilities in the market have helped revive discussion on the strength of the connection between macroeconomics and the financial sector, as well as the role of shocks as an amplifier of the real side of economy, which some assets end up assuming. Therefore, this article contributes to the comprehension of economic dynamics and macro-financial linkages during financial and non-financial stress regimes.

A series of studies sought to investigate the effects of economic policies and understand economic dynamics during periods of

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[1] Bernanke et al. (1999) displayed a mechanism in which endogenous developments in the credit market worked as amplifiers and propagated the shocks to the macroeconomy. Next, Rigobon and Sack (2003) sought to determine the relationship between the prices of assets in the financial market with monetary policies, identifying that movements on the stock market have a significant impact on the short-term interest rate.

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adversity in the financial market, such as the work of Davig and Hakkio (2010) and Hubrich and Tetlow (2015) for the United States, as well as that of Aboura and Van Roye (2013), which demonstrated that episodes of financial instability are associated with a significant decline in French economic activity. Mittnik and Semmler (2013) uses a threshold autoregression(TAR)-based regime model to investigate how financial crises overflow into the real economy in the United States as well as five European countries. In turn, Dahlhaus (2017) uses a model with smooth transitions, allowing the observation of a non-linear dynamic in the propagation of monetary policy in accordance with US financial conditions from 1970 to 2009. Both Dahlhaus (2017) and Hubrich and Tetlow (2015) focus on the effects of conventional monetary policy. Even though Hubrich and Tetlow (2015) highlights that a sharp reduction in federal funds rate at the start of the crisis in 2007 would have had relatively small effects on real activity, Dahlhaus (2017) finds that an expansionary monetary policy during episodes of financial stress has stronger effects on macroeconomic variables than during normal times.[2] Finally, Dovern and van Roye (2014) studied the effects of financial stress on international business cycles from a global vector autoregressive model, enabling the capture of overflow between countries.

Even though the international literature already points to the economy's different behavior in these moments, these studies are concentrated in the analysis of developed markets and lack of research that may indicate the financial market's overflow to the dynamics of the real economy in developing countries.[3] In this way, the main purpose of this study is to investigate the differences in macroeconomic dynamics during periods of instability in the Brazilian financial market in comparison with periods of stability through a Markov-Switching Bayesian Vector Autoregressive Model (MS-VAR). With this framework, we contribute to the macro-finance literature, demonstrating linkages between financial stress and real economy dynamics. Furthermore, we show that the effects of policy responses differ considering a financial stress or a non-financial regime, as demonstrated by the developed countries ' literature.

In order to investigate the effects of financial stress on the economy, we need a measure of financial stress. Thus, a secondary objective is to formulate an index capable of synthesizing the behavior of the financial market, making it possible to highlight historically recognized periods of uncertainty. The development of financial market instability indicators became more common after the 2008 US subprime mortgage crisis. Several researches have already developed measures of financial stress, such as Brave and Butters (2011) and Hakkio and Keeton (2009) for the US, and have used it to examine real activity and financial stress linkages (Davig & Hakkio, 2010) and spillover effects among countries (Apostolakis, 2016). We follow Dahlhaus (2017); Hubrich and Tetlow (2015); Aboura and Van Roye (2013); Davig and Hakkio (2010), among others, in the use of a financial index to understand the shock effects of different financial instability periods. This class of indexes takes into account a wide range of information about the financial system that is summarized by a common factor. Since there is no such variable with these characteristics for Brazil, an important part of our work is to develop a Financial Stress Index for this country.[4]

Thus, this paper contributes to the recent literature which seeks to investigate the relationship between periods of adverse effects on the financial market with the dynamic macroeconomic environment. Such an approach is practically nonexistent in studies that shed light on the Brazilian market, the same way that there is a need for periodical indicators and objectives that indicate the level of the Brazilian financial market, as is formulated in this work. Under such auspices, the next section will present the theoretical review, addressing the relationship between the financial market and macroeconomic dynamics. In Section 3, the study will present the set of methodological tools and data utilized, followed by the results and the conclusion.

2. Financial market and macroeconomic dynamics

The financial market can affect the real economy in two different ways. First, it is possible to observe how firms will make decisions to invest in face of uncertainty, since they may postpone investments while they wait for market stabilization, following the approach of Real Options Model pointed out by Bernanke (1983); Bloom, Bond, and Van Reenen (2007) and Baum, Caglayan, and Talavera (2010). In accordance with the theory of the real options, the effect of a financial crisis can be understood as a time of instability, which will affect agents' investments and produce effects both in governmental policies and in economic cycles. Secondly, firms can be affected by financial turbulence in terms of the limited possibilities to borrow, generating further restrictions in the credit market, as suggested by the accelerator financial model in Bernanke, Gertler, and Gilchrist (1999) and Davig and Hakkio (2010). With increased uncertainty from tensions in the financial market or with the increase in risk variance in a specific industry, most fragile economic conditions affect balance sheets and, consequently, the ability to obtain credit. Banks will then increase the external financial premium, fearing that many firms will break. This situation will in turn decrease investments and production companies, generating new uncertainties and potentially increasing the damage to macroeconomic fundamentals.

Despite the existing theoretical development, Borio (2014) has highlighted that until 2000, the literature had no clear measurement of the importance of financial factors' impact on understanding business fluctuations. Currently, the work of

[2] Dahlhaus (2017) argue that Hubrich and Tetlow (2015)'s and her results are not contradicting once they are focusing on a systemic analysis, while her paper studies the unexpected part of monetary policy.

[3] With a few exceptions, such as Pitterle, Haufler, and Hong (2015) and Apostolakis and Papadopoulos (2014).

[4] There are no consensus regarding the usage of a Financial Stress Index or a Financial Condition Index. Therefore, we decided to follow Hubrich and Tetlow (2015) and work on a Financial Stress Index for the analysis.

Claessens, Kose, and Terrones (2012) and Drehmann, Borio, and Tsatsaronis (2012) and Aikman, Haldane, and Nelson (2015) empirically consolidated the relationship between business cycles and financial cycles. These authors share the understanding that financial cycles or credit cycles operate on a low frequency (medium-term), different from business cycles (commonly characterized with a duration of up to 8 years) and are, therefore, longer. Drehmann et al. (2012) indicated that the peaks of the financial cycle are associated with financial crises. In turn, Claessens et al. (2012) showed that the duration and amplitude of recessions and recoveries are formed by the connection between business and financial cycles, highlighting the fact that recessions accompanied by financial upheaval tend to last longer and be more profound. The authors observed that recessions accompanied by contractions in the stock market are associated with a further decline in production during the recession. Finally, the results of Aikman et al. (2015) are complementary in this sense because they also highlight the strong relationship between credit/GDP ratio (which the authors used to formulate the credit cycle) and stresses on banking.

In this sense, Borio (2014) highlighted that the measurement of financial cycle and perception of the relevance of financial factors on macroeconomics brings challenges to economic policies. These challenges are especially provocative in the case of monetary policies, which risk being overwhelmed and are liable to losing their credibility and effectiveness with time. However, the traditional analyses of economic policies' effects do not take into account the difference between periods of crisis and stability. This differentiation is justified, for example, by evidences that there are low inflation rates in periods of financial markets' expansion as well as growth in the credit supply (Christiano, Ilut, Motto, & Rostagno, 2010).

3. Methodology and database

3.1. Financial stress index

Since the crisis of 2007–2008, economists have developed a series of statistical indicators to attempt to measure financial instability. These indicators estimate latent conditions that are not observed but rather are formulated from other variables related to the financial sector. These indicators also seek to capture threats to the market, but there is no consensus in the literature regarding the meaning of financial stress (Kliesen, Owyang, & Vermann, 2012). For Brave and Butters (2011, 2012), financial stress is simply a synonym of instability, while for Hakkio and Keeton (2009), financial stress can refer to uncertainty about the values of assets, uncertainty as to the behavior of investors, asymmetry of information, increased demand for low-risk assets, or increased demand for highly liquid assets. Kliesen et al.(2012) analyzed 18 definitions and interpretations of the term, summarizing financial stress as a series of conditions in which the market changes its expectations about future losses, asset values, and economic activity.

To formulate an index of instability in the Brazilian financial sector, references that were explored include the Federal Reserve Board of St. Louis Financial Stress Index (STLFSI), created by Kliesen and Smith (2010); Kansas City Financial Stress Index (KCFSI), created by Hakkio and Keeton (2009); the Aboura-Diebold-Scotti Business Condition Index (ADS) of the FED of Philadelphia, created by Aruoba et al. (2009); the National Financial Conditions Index (NFCI) of the FED of Chicago, created by Brave and Butters (2011), and other indexes developed in the literature. As the survey about financial stress indexes by Kliesen et al.(2012) indicates, there is a conceptual difference between the financial stress (FSI) and the financial conditions indexes (FCI). A FSI tries to monitor financial instability by creating a time series of values in which increases indicate a higher likelihood of a crisis, while a FCI considers a wider set of information, including nonfinancial variables in order to measure financial instability. For the purpose of this paper, a FSI is designed to capture the level of fragility in the financial system in Brazil.

To formulate the financial instability index, a state-space Dynamic Factor Model (DFM) was used; this model was demonstrated in Stock and Watson (2011) and applied by Aruoba and Diebold (2010) and Brave and Butters (2011) in a similar way to what this work proposes. The premise of this model is that some dynamic factors latently lead the co-movement of vectors of the high-dimensional time series, which is also affected by a vector of disturbances with zero mean.[5] These disorders can be considered idiosyncratic because they arise from errors of measurement and specificities of a time series (unexpected events).

Following Stock and Watson (2011), the state space representation of the dynamic factor model is,

$$X_t = \lambda(L)f_t + \varepsilon_t \tag{1}$$

$$f_t = \Psi(L)f_{t-1} + \eta_t, \tag{2}$$

where X_t is the vector of observed series, f_t represents the dynamic latent factors and ε_t disturbances with zero mean. In addition, it assumes that there are N series, being X_t and ε_t $N \times 1$, and q dynamic factors, then f_t and η_t are $q \times 1$. l is a lag operator and $\lambda(L)$ and $\Psi(L)$ are the lag polynomial matrices $N \times q$ and $q \times q$, respectively. The load of the dynamic factor series i, where X_{ti}, is represented by $\lambda_i(L)$, and the common component is $\lambda_i(L)f_t$.

[5] We estimate one- and two-factor models. Since results are similar and we used only the first factor, we present results for the one-factor model here.

It assumes that processes (1) and (2) are stationary, and disturbances are assumed to be uncorrelated with innovations of factors in all leads and lags, i.e. $E(\varepsilon_t \eta_{t-k})' = 0$ for all k, and they are also mutually uncorrelated among themselves, $E(\varepsilon_{ti}\varepsilon_{js}) = 0$ for all s since that $i \neq j$. Thus, one of the advantages of using DFM is that, normally, q is much smaller than N, enabling to make more accurate forecasts using individual variables from the factors f_t.

3.2. Model specification

After the formulation of the index summarizing the financial sector's activities, it will be necessary to analyze this series to identify stress periods. Therefore, a Bayesian Markovian Switching Vector Autoregressive Model (MS-VAR), as developed by Sims, Waggoner, and Zha (2008), was used. As mentioned previously, this model was used by certain authors to analyze economic policies during periods of financial instability .[6] This methodology appears the most appropriate to define periods of crisis, as it enables the identification of non-linearity in the process. After the definition of the arrangements, the effects of economic shocks in periods of stability and instability can be observed from impulse response functions of an auto-regressive vector model in conjunction with regime changes.

A Markovian process model is a process in which a classic stochastic random variable depends on time. This process will be discrete or continuous, depending on the state s_t of this variable. The likelihood that s_t is equal to i since s_{t-1} and j can be represented by the Markovian transition matrix $P_{ij} = (p_{i,j}) \in M(k \times k)$, i.e.:

$$Pr(s_t = i | s_{t-1} = j) = p_{ij} \tag{3}$$

$$P = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{k1} \\ p_{12} & p_{22} & \cdots & p_{k2} \\ \vdots & \vdots & \ddots & \vdots \\ p_{1k} & p_{2k} & \cdots & p_{kk} \end{bmatrix} \tag{4}$$

where the elements of each matrix column P added 1, $\sum_{i \in M}^{k} p_{i,j} = 1$, and $p_{i,j} \geq 0$.

Models with regime switching are considered a generalization of a finite order autoregression for the vector of time series $y = (y_1, \cdots, y_T)$ of order k and T observations and insert regime changes, the parameters of the process above (intercept, variance and coefficient) depending on the regime amendment. In addition, models of this class may also be submitted by incorporating the possibility of a vector column of exogenous variables and are deterministic in time t, which can be represented by (Sims et al., 2008, p. 265):

$$y'_t A(s_t) = \sum_{i=1}^{\rho} y'_{t-1} A_i(s_t) + z'_t A_0(s_t) + \varepsilon'_t \Xi^{-1}(s_t), \tag{5}$$

where ρ is the lag length, y_t is the column vector of endogenous variables, z_t is the column vector of exogenous and deterministic variables, ε_t is the column vector of unobserved random shocks, $\Xi(h)$ is a diagonal $n \times n$ matrix for $1 \leq h \leq k$, $A(h)$ is an invertible $n \times n$ matrix, $A_i(h)$ is an $n \times n$ matrix for $1 \leq h \leq k$, and $A_0(h)$ is an $m \times n$ matrix for $1 \leq h \leq k$.[7]

3.3. Data

To identify the most appropriate variables to formulate the financial instability index, it is sufficient to observe those that are applied in other, similar studies. Most of the variables used in this paper are also common in the literature and are used in similar studies, as demonstrated by Kliesen et al. (2012). The authors also demonstrated the complete lack of consensus in the literature in terms of the variables that should make up a financial instability indicator, even in work that analyzes the same country, in this case the United States. However, as in other studies, they point to the formatting data that is divided into groups according to its characteristics.

This way, variables corresponding to those used by the indexes cited were selected, and other indicators that could qualify the results were also inserted. Moreover, we incorporated indicators of the "external market" through which the index could integrate the Brazilian and international markets. Seeking to facilitate the subsequent analysis, data was divided into three groups: Risk, banking, and external. The tables that synthesize the content of each group are located in Appendix A.

3.3.1. Risk group

First, data was collected from the capital market that could demonstrate risk in the financial system. The selected series are detailed in Table A1. The first column of the table (A1) hosts the code by which the data were called, followed by the description of each variable, the frequency of data, the original source, and the period of the original series' beginning and end. In the case of that group, all data is observed at the same frequency (per day, five days per week). The variables vol_ibov, b_Corp, and v_cambio were created based upon other observed data. We also emphasize that the variables swapdi and gold are available in a smaller time interval than the one analyzed, a fact that can be overcome by using the dynamic factor model combined with the EM

[6] such as Davig and Hakkio (2010); Aboura and Van Roye (2013); Hubrich and Tetlow (2015).

[7] Equation (5) can be written in the following compact form: $y'_t A(s_t) = x'_t F(s_t) + \varepsilon'_t \Xi^{-1}(s_t)$ for $1 \leq t \leq T$, Let $\underbrace{x_t}_{\rho n \times 1} = \begin{bmatrix} y_{t-1} \\ \vdots \\ y_{t-\rho} \\ z_t \end{bmatrix}$ and $\underbrace{F(s_t)}_{(\rho n+m) \times n} = \begin{bmatrix} A_1(s_t) \\ \vdots \\ A_\rho(s_t) \\ A_0(s_t) \end{bmatrix}$

algorithm.

The variable called "swapdi" characterizes the spread between the maturities of 30 days and 10 years and represents the slope of the yield curve, an indication of the expectations for future interest.[8] The insertion of gold in the analysis lies in understanding whether it serves as a store of value in times of financial turbulence. Furthermore, investors resort to gold in periods of great monetary devaluation.[9] The Ibovespa index stock return reflects expectations surrounding overall market profitability. The beta of the corporate sector was used to represent companies' capital costs; for this factor, non-financial enterprises and non-banking firms that belonged to the IBX50 on 15/04/2015 were considered. As the IBX50 considers fifty available actions that are negotiated, only those that were already negotiated at the beginning of the period under analysis, 03/01/2000, were selected, thus totaling twenty-one actions of nineteen companies [10].

In addition, two variables of volatility make up the risk group. Volatility is a way to measure the risk because periods with high volatility suggest greater fluctuations in the market and therefore greater risk. The exchange rate volatility is a common variable for financial stress indexes for countries other than United States.[11] The specifications for beta and volatility's calculation will be presented in the next section, together with the specifications of the model ARMA/GARCH.

3.3.2. Banking group

The data grouped under the banking sector are in the Appendix as Table A2. The first two series originate the property of monthly consolidated by the Brazilian Central Bank. The first variable, bfin, represents the total funding transferred by Brazilian banks divided by total assets, while srisco represents the spread between operations at Risk Levels A and C. Though many FSIs use banking data, these variables may vary depending on the Central Bank aggregation. At the same time, these two variables summarize variation in banking capital and banking lending, and risk spread. Rising financial instability tends to increase uncertainty and weaken the real economy through a variety of transmission mechanisms, including a reduction in bank lending and balance sheet effects that reduce the value of a firm's collateral.

For the sector's volatility and beta, it was necessary to group the bank's shares performance, considering stocks of banks in the IBX50 until April 2015. This way, four stocks were selected.[12] A description of the variables and their sources and frequency are in Table A2.

3.3.3. External group

Finally, the third group is composed of variables that had the capacity to capture characteristics of the international financial market as a whole, as laid out in Table A3. The Cross-border claims (credit) is part of the Consolidated Banking Statistics compiled by the Bank of International Settlements (BIS). The purpose of this variable is to analyze the international component of credit for the assessment of global liquidity conditions. We expected that the higher the global liquidity, the smaller the financial stress. This belief is grounded on the theoretical foundation developed in the second section of the paper. This series considered the variation of the total credit granted by banks and other sectors of the economy to the non-financial sector in over forty countries in relation to the same quarter of the previous year. The variable "yield" refers to the long-term and short-term yield risk premium of the United States (120 months and 1 month, respectively), commonly used by other authors. The VIX represents short-term expectations of the volatility of prices of the options of the suffix S&P 500, supplied by the Chicago Board Options Exchange (CBOE).

In turn, the TED spread signifies the spread between the LIBOR and the American Treasury Bill for 3 months, both priced in US dollars. This series captures the credit risk, since T-Bills are considered risk free and the LIBOR (London Interbank Offered Rate) is calculated on the basis of the rates of interest intrabanks. Finally, the last two indexes are made up of aggregates of twenty-one emerging countries and twenty-four developed countries, respectively, and are computed in dollars by the NASDAQ.[13] The NQEM and NQDM, NASDAQ Emerging and Developed Markets Index have the same purpose of the national stock market returns used in several studies, including ours. We understand that, since NQEM and NQDM aggregate indexes of many countries, they would be able to capture an upcoming global stress event. Furthermore, with the distinction between emerging and developed markets, we can understand if there is a decoupling of shocks from countries in different stages of development.

3.4. Procedures and data treatment

Before introducing the results, we will report the data treatment. To estimate the exchange rate's volatility, the Ibovespa and banking sector used an Autoregressive Conditional Heteroskedastic model (ARCH/GARCH) because, in view of applications used in the literature, models from the ARCH family have the purpose of modeling and predicting the financial market's volatility. However, as

[8] For a discussion on the interest curve in Brazil, see Stona, Amann, Morais, Triches, and de Morais (2015).

[9] Baur and McDermott (2010) indicated more evidence of gold's importance to movements of international risk, showing, for example, that investors react to extreme shocks of short duration with the purchase of gold.

[10] Ambev S/A (ABEV3), BRF SA (BRFS3), Petrobras (PETR4 e PETR3), Vale (VALE5 e VALE3), Embraer (EMBR3), Pão de Açúcar-CBD (PCAR4), Telefônica Brasil (VIVT4), CEMIG (CEMIG4), Souza Cruz (CRUZ3), Gerdau (GGBR4), Tim Part. S/A (TIMP3), Lojas Americanas (LAME4), Suzano Papel (SUZB5), SABESP (SBSP3), Siderúrgica Nacional (CSNA3), Natura (NATU3), Brasken (BRKM5), Usiminas (USIM5) e OI (OIBR4).

[11] See Kliesen et al.(2012).

[12] The data of profitability is equivalent to the average daily stock return.

[13] emerging countries considered by the NEQM (NASDAQ Emerging Markets Index) are: Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, Indonesia, India, Morocco, Mexico, Malaysia, Peru, Philippines, Poland, Russia, Thailand Turkey, Taiwan and South Africa. On the other hand, the NQDM (NASDAQ Developed markets Index) considers the following developed countries: Austria, Australia, Belgium, Canada, Switzerland, Denmark, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Ireland, Israel, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Portugal, Sweden, Singapore and the United States.

cataloged by Bollerslev (2010), there are over 130 variations of the model. Given the difficulty and the space limitation of describing all variations, only six specifications were tested: the standard GARCH model of Bollerslev (1986); the exponential (eGARCH version), Nelson (1991); the model GJR-GARCH, Glosten, Jagannathan, and Runkle (1993); the model arch with asymmetric power (Ding, Granger, and Engle, 1993); the model cGARCH, Lee and Engle (1993) and the tGARCH, Zakoian (1994).

This way, thirty-six specifications for model $ARMA(m, n)$ to $M = 0.1, \ldots, 5$ and $n = 0, 1, \ldots, 5$ with $\mu \neq 0$ were tested, whereas thirty-five specifications were tested for $\mu = 0$. Conditional distributions were then tested for a standard GARCH model, observing the univariate normal distribution (norm), generalized error distribution (GED), the Student-t (STD), the skewed versions of these three distributions (snorm, sGED and sstd) as described by Ferreira and Steel (2006), and normal inverse distribution Barndorff-Nielsen (1997).[14] Finally, the six ARCH/GARCH models mentioned earlier were tested, in which the BIC, AIC, HQIC, and SIC criteria were observed. The Ljung-Box test was conducted to check if there was any autocorrelation in residuals, and the ARCH-LM test was conducted as well.

As mentioned, the definition of the volatility model that was used took place in three steps. For the Ibovespa, it was first established that the specification that minimized the BIC was $ARMA(0, 3)$ with $\mu = 0$. Then, it was found the normal inverse distribution (NIG) whilst minimizing the four criteria observed in comparison with the other distributions tested. Finally, by observing the same criteria and the Ljung-Box and ARCH-LM tests, it was concluded that the most appropriate model to investigate the volatility of the Ibovespa would follow a $ARMA(0, 3)$ process for the equation of measurement and $GJR- GARCH(1, 1)$ with inverse Gaussian distribution of errors. Following the same process, the banking sector's volatility was defined by a $ARMA(0, 3)- eGARCH(1, 1)$ model with distribution of errors std and the exchange rate volatility by $ARMA(0, 1)- eGARCH(1, 1)$ with distribution of sstd errors, both with $\mu = 0$.

The betas of corporate and banking sectors were defined based on the CAPM.[15] In general, the beta represents the sensitivity of certain stock in the face of market risks; with this, there is an expectation that an increase in beta would contribute positively to financial stress. Despite the fact that the original model considers the parameters constant over time, betas of the CAPM can be observed in conditional form, from the assumption that the betas vary in time (Mergner, 2009).

Thus, there are various possibilities for determining the betas, the most common ones are the Kalman filter based on a state-space CAPM and the models of the GARCH family.[16] In Choudhry and Wu (2008) and other studies cited by the authors, the models estimated by the Kalman filter are more efficient than others. In this way, the following equation was used (Choudhry & Wu, 2008, p. 677), $R_{ti} = \alpha_t + \beta_{ti} R_{Mt} + \varepsilon_t$, such that R_{ti} and R_{Mt} are, respectively, the return of the sector's stocks *i* and the return of the market portfolio in time *t*. α_t is the intercept and ε_t is errors. Then, aiming to submit the transition equation, it is necessary to determine which stochastic process will determine the betas. Following Choudhry and Wu (2008) and Mergner (2009), it is assumed that the beta follows a random walk, $\beta_{ti} = \beta_{ti-1} + \eta_t$. Therefore, such equations constitute a model of state-space in which the Kalman Filter can be applied to estimate the series of conditional betas, which was used to estimate the beta of the corporate and banking sectors.

4. Results

In this section, we will present the results of the models that were performed, analyzing the results for the financial instability index estimated by the dynamic factor model and the effects of economic policies in periods of financial instability using MS-VAR.

4.1. Brazil financial stress index

By following the procedures adopted by Aruoba and Diebold (2010), we used monthly frequency data and avoided working with matrices variables in time and state vectors of high scalability, which also helps maximize transparency. The high-frequency data was conditioned by a monthly average. One of the advantages of working with a dynamic factor model in a state-space approach is the relationship with the missing data for both variables in low frequency as for a series of different sizes, as discussed by Durbin and Koopman (2001) and Harvey (1989). In addition, the data was standardized and its non-linear trend was removed. The results were estimated with the maximum likelihood EM algorithm.[17] Two types of arrays of variance and covariance of errors ε_t were tested in the Equation (1), with the same variance and with different variance diagonal. A Likelihood Ratio test support the assumption of different variance diagonal, and the first factor of this specification gave rise to the Brazilian Financial Stress Index (BFSI) that will be presented here.

As with other indicators of this type in the literature, the BFSI is a weighting of financial indicators in which the load of the factors (λ) exposed in Fig. 1 reflects the weight of the variables in its movements. Given this, the variables with the highest weight are those that have historically had greater systemic relevance. In this way, we recognize the importance of volatility variables to positive variances, as well as the data from external groups VIX and TED. The betas of the corporate and banking sectors also appear with positive loads, following expectations, since these are measures of risk. It is also interesting to note that the Brazilian and American yield spread, swapdi and yield, respectively, presented $\lambda > 0$, and that the effect of Brazilian spread on the local market's instability is greater than that of American spread. Finally, the relationship between total financing and banking assets suggests a greater variance in the indicator when

[14] For more details, see Ghalanos (2014).
[15] Capital Asset Pricing Model.
[16] other alternatives are the use of a model of stochastic volatility and models that assume a Markovian process.
[17] convergence parameters of the model were set on $\text{logLik}_{i+1} - \text{logLik}_i < 0.001$ and test $log - log = 0.0001$, with a minimum of 200 and maximum of 10,000 interactions. For more details, see Holmes, Ward, and Wills (2012).

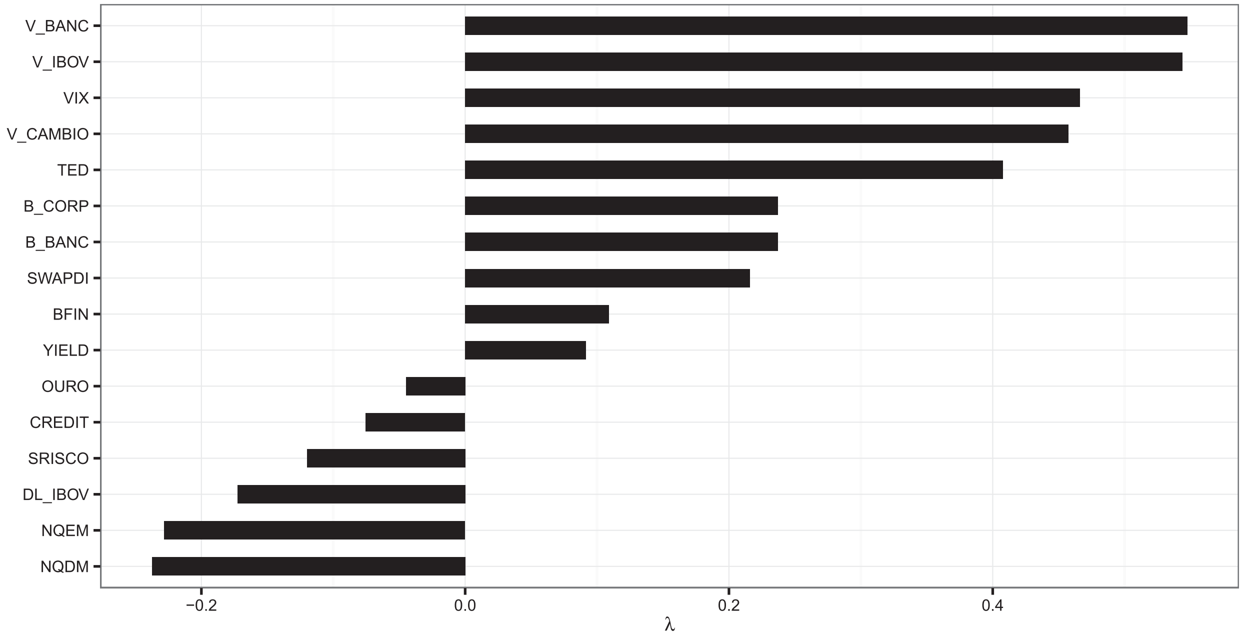

Fig. 1. Ranking of the indicators of the BFSI per charge of factors.

Brazilian banks increase funding granted above their capacities.

On the other hand, a fall in the return of the Ibovespa and international markets would increase the Brazilian financial system's instability. This would affect the spread of hazard operations of Brazilian commercial banks (srisco), making them assume a greater risk when the financial scenario is less rigid. The same goes for credit interactions between countries (credit), which is an indicator of instability when it becomes more restricted. Finally, the small but negative result for the gold price indicates that an increase in the price reflects a drop in the financial system's instability.[18]

These results follow our expectations in that the increased volatility and credit risk as well as the reduction in liquidity lead to a more rigid financial scenario. In addition, the BFSI has characteristics similar to those found by Aboura and Van Roye (2013), in that the volatility of the banking sector was the most positively relevant and the return of the French stock exchange was among the most minor. For Brave and Butters (2011), the highest positive load was the volatility of the S&P 500 (VIX) and the biggest negative weight was the return of S&P 500. Thus, based on the literature, the volatility of the local stock exchange and its return are among the most important factors for the BFSI. However, this work is distinguished from the rest of the literature in that it considers existing interactions with the international market, as it perceives the relevance of external factors to the Brazilian financial system's instability.

After an analysis of the factors that influence the BFSI ′s variance, the index is presented and the relevant periods in the historic setting are analyzed. For this study, the interpretation of these periods observed the reports of financial stability by the Central Bank of Brazil. Furthermore, it should be noted that the index presented in Fig. 2 is expressed in relation to the standard deviation of the sample so that values close to 1.00 are associated with adverse conditions in the financial system, when there is greater stiffness and insecurity, while values closer to −1.00 describe a period of relaxation, when there is a more tolerant and flexible system.

The first point that should be highlighted is the BFSI ′s value in April 2001, which surpassed the mark of 1,2605. The world economy was hit by a severe recession after the speculative crisis triggered in the mid-2000s, when the BFSI surpassed 1000 for the first time. The financial market has faced confidence shocks and increases in risk aversion. In addition, in May 2000, the peak of the crisis of the American stock market's dotcom bubble is visible with the burst of the NASDAQ index. In the two subsequent months, the BFSI accused the Brazilian financial market of instability. In addition to these events, in June 2001 the American company WorldCom, the majority shareholder of Embratel in Brazil, applied for bankruptcy. Two months earlier, the BFSI was between 0.75 and 1.26, probably because of rumors in the market. The last historical fact that should be highlighted in relation to this first moment is September 11, which caused instability in the international market and, internally led the BFSI to triple in size; it reached 1.26 in that month.

Next, there is the second largest peak of the series, which occurred between July and October 2002, with the BFSI = 2,0939 in August. This movement can be explained in part by internal matters in Brazil such as the electoral process, which generated uncertainties, greater perception of credit risks and the retraction of foreign investments. The analysis of the BCB that “the financial market

[18] By virtue of Brazil's status of an emerging market, this result does not differ from the literature on the topic, such as the one pointed by Baur and McDermott (2010), because authors indicate that trends of monthly losses on the stock market do not drive investors' response. Furthermore, the effects identified by the authors in emerging markets, besides information sought in high frequency, were lower. Nevertheless, such a result merits further study for a better understanding of these effects that contrast with the traditional economic reasoning.

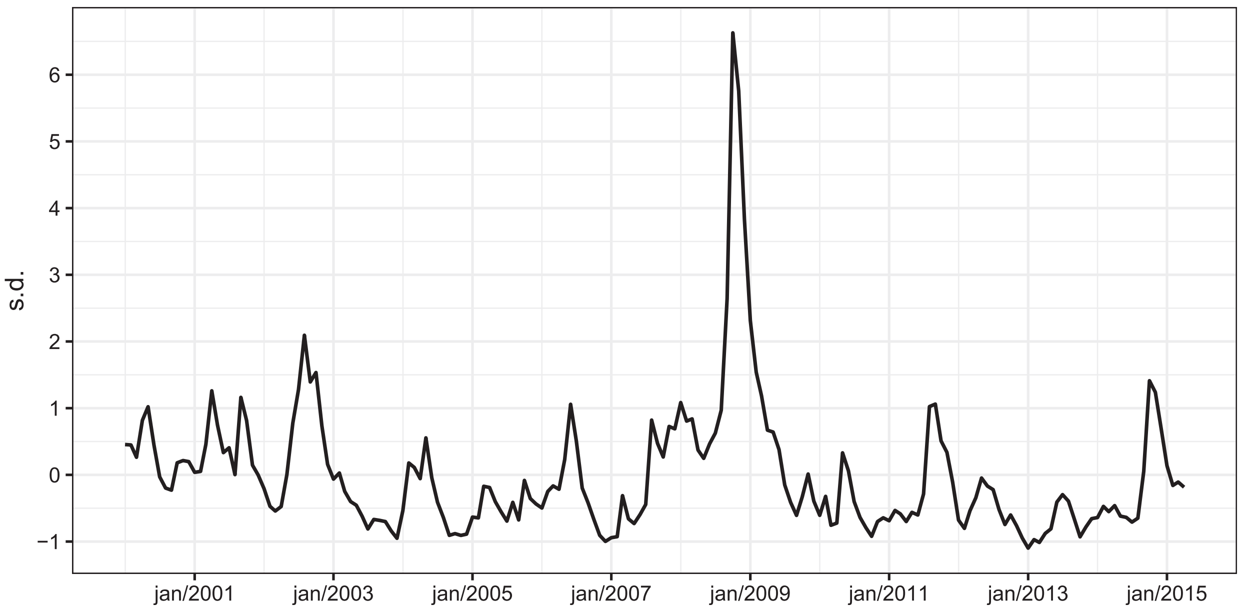

Fig. 2. Brazilian Financial Stress Index (2000–2015).
Note: The Brazil Financial Stress Index (BFSI) is the first factor of a Dynamic Factor Model standardized with zero mean and unit standard deviation. Values close to unit are associated with adverse conditions in the financial system, while values close to − 1.00 are considered periods of relaxation.

has experienced a phase of relative tranquility and of renewed confidence until March [2002]" (BCB, 2002) is portrayed in the BFSI with an index below 0 in the first quarter of that year, demonstrating the accuracy of this analysis.

The crisis in the American real estate market that broke out in mid-2007 demonstrated its first signs in the BFSI in August of that year, with the index exhibiting a deviation of 0,8217. However, only in January 2008 did it exceed the mark of a deviation point. Before stepping into the period considered the peak of the financial crisis, we must highlight other results of the BFSI that demonstrate its accuracy, in particular in April and May 2008, when Brazil reached the investment grade by international agencies of investment risk evaluation and the index dropped back to 0,3722 and 0,2476, respectively. However, the credit crisis intensified as of November 2008 as analyzed by BCB (2008), and the BFSI reached deviation of the mean of 2,6423. At this moment a process of retraction of liquidity in the international capital market also occurred as well as high volatility in domestic interest rates and a decline in the volume and value of the Brazilian stock market.

The pinnacle of the crisis as identified by BFSI took place in October 2008, reaching a deviation of 6,6282. In the first quarter, the index was not below the unit of deviation, demonstrating that the perception of the international financial crisis and its effects in Brazil were robust and lasted at least seven months. In May 2009, the BCB (2009) underlined that the unfolding crisis was still uncertain, with a credit market still operating under out of the usual patterns, with an increase in national credit operations to the detriment of global restrictions.

It is worth comparing the BFSI with two indicators formulated for the US, the St. Louis Fed Financial Stress Index (STLFSI) and the Chicago Fed's National Financial Conditions Index (NFCI) .[19] However, the divergence between the two indicators, even those formulated for the same country, is noteworthy, since they differentiate in terms of data and methodology. Fig. 3 presents the comparison of these indices with the Brazilian indicator formulated here.

One of the main differences between these two indicators and the BFSI is that the BFSI integrates variables of the international market, while the other indicators observe national variables of the North American market only. For this reason, the comparison allows one to observe cases in which the instability referenced by the BFSI is representative of uncertainties in the Brazilian market, as in 2006 and mid-2014, when international indicators are at normal levels, but the Brazilian indicator reaches a deviation. Perceptible behavior is more apparent in the BFSI and STFSI, but the three indices all point to the crisis of 2008. For this crisis in particular, comparison of the indicators illuminates the fact that in the US its effects were perceptible since the end of 2007, while in Brazil only since mid-2008. It also reveals that, although the crisis was shorter in Brazil, its effect was greater there than in the USA.

4.2. Economic dynamics in periods of financial instability

The literature suggest that periods of high instability lead to changes in business cycles, in the behavior of consumption and investment, and in the dynamics of macroeconomy. Thus, economic policies would have different effects in periods of greater and lesser

[19] As the NFCI started in 1973, the sample selected from 2000 to 2015 was readjusted and called NFCIA, for better comparison.

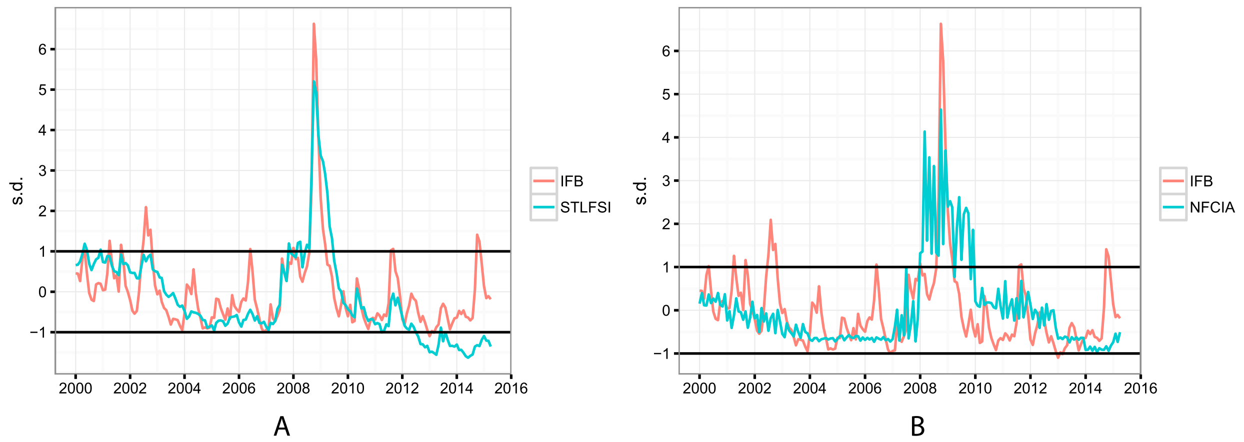

Fig. 3. Comparison of financial stress indexes.

stability in the financial market. Therefore, the last exercise to be conducted relies on the research on the effects of greater financial stress in the economy a the other way around.

It is assumed that the BFSI is regime dependent and that shocks may suddenly occur. Therefore, an MS-VAR with five variables and identified with a lower triangular matrix Cholesky decomposition is formulated. It was defined $y_t = [\text{BFSI INF M S C}]'$ in which, besides the index of Brazilian financial instability (*BFSI*), the IPCA provided by IBGE was used to represent inflation (*INF*), the growth of the monetary aggregate M2 (*M*) - understood as the currency stock, currency held by the public and demand deposits, M1, plus term deposits - supplied by the BCB, the realized Selic interest rate (*S*) by BCB-Demab, and expenditure on household consumption (*C*), which will represent the economy's real activity. Because of the lack of series that would represent consumption at a monthly frequency and covering the period analyzed, the methodology of Aruoba and Diebold (2010) was applied with the quarterly index of household consumption expenditure from IBGE and the average monthly income of families from the Brazilian Central Bank (BCB), filling in the months in which the consumption of families was not observed by the IBGE quarterly index. The series were standardized and had trends removed. The MS-VAR was Bayesian estimated according to the model formulated by Sims et al. (2008), and the priors used are described in Table B1 in Appendix B.

Periods of stress were defined as being characterized by a change in the status of the coefficients and variance, allowing the existence of two states and making an interpretation of the results more direct. The model estimates the probability of being in a given state from the data supplied and not whether the economy was in a recession. Therefore, considering the series used and the restrictions imposed,

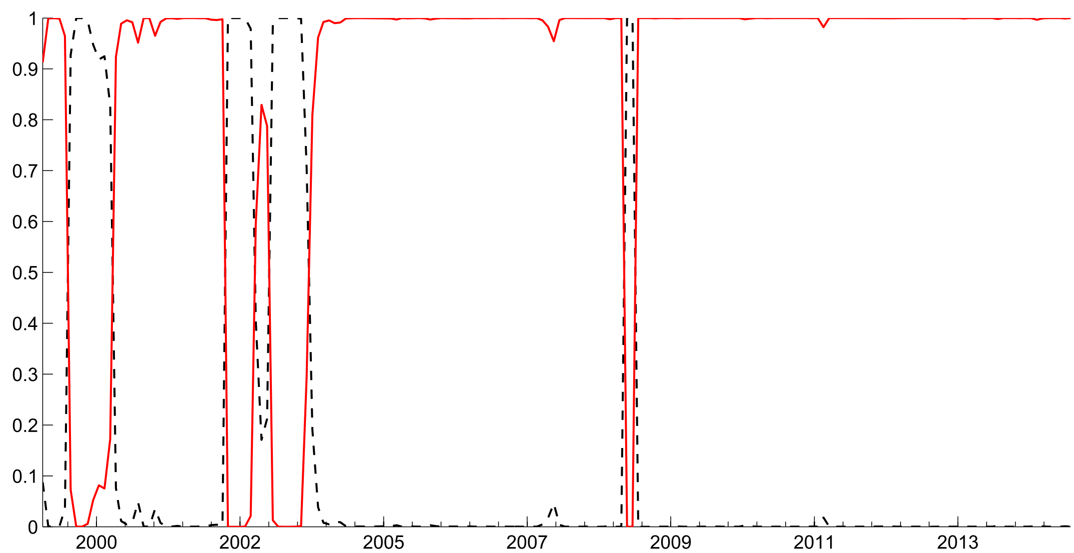

Fig. 4. Probability of stress events in the Brazilian financial system.
Note: Smoothed regime probabilities. The first regime (black dashed-line) is the stress regime and the second regime (red line) is the non-financial stress regime. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

the regimes are characterized by periods of stress and normality in terms of the financial system. Fig. 4 shows the probabilities for the two regimes defined. The probability of remaining in the stress regime is 0.90 and in a non-financial stress regime, 0.97. The transition probability from a stress regime to a non-financial stress regime is 0.09 and 0.02 on the opposite direction. These results demonstrate that even though a financial crisis is a rare event, it is also a highly persistent state.

In the comparison between these periods of high stress with the movements of the BFSI (Fig. 2), it is clear that not all occurrences in state 1 (regime of financial stress) coincide with the peaks in the BFSI. In 2000, the peak of the BFSI anticipated the regime change in a month. In 2002, it was also possible to recognize anticipation when the index exceeded a deviation in July, remaining at this level until October, when the regime change occurred precisely in that month. The last moment of analysis where the BFSI is able to anticipate a high increase in the probability of regime change was in August 2008, one month before the probability of being in a regime of stress was 99.99%.

At the same time, there are periods in which the index exceeds a deviation of the mean but no regime changes occur, as in June 2006, December 2007, August 2011 and October 2014. Finally, there is one case when the probability of regime change is higher then 90% but the BFSI is below the one standard deviation threshold, in June 2001. However, this period can also be interpreted as a continuation of the regime started on October 2001. It follows, then, that periods of stress in the financial system must have a common behavior of stress in terms of the financial market and the rest of the economic system in addition to this relationship between the index and the periods that the estimation identifies as regimes of instability in the market.

The relationships of variables in high stress and normality regimes can be observed on Fig. 5, which displays the impulse response functions to a shock to the BFSI. The first important point is the difference in the magnitude of shocks in periods of system instability. A similar effect was observed in the experiment of Hubrich and Tetlow (2015) and Mittnik and Semmler (2013). It is worth emphasizing this fact because it demonstrates that mistaken policies in these periods are more harmful to the economy over the long term, since they are also more persistent. Still, the results for an increase in stress during normal periods of Brazilian data represented by the dashed line of Fig. 5 are similar to those of Hubrich and Tetlow (2015). It is possible to notice a slight increase in the money supply until around six months after the shock, with a marginal drop in the federal interest rate, inflation and relatively small negative effects on real activity represented by expenditures with consumption, proving that financial stress has slightly relevant effects on the economy in normal times.

Specifically on the topic of the results of the impact of financial stress on real activity, the results for Brazil are the same as those

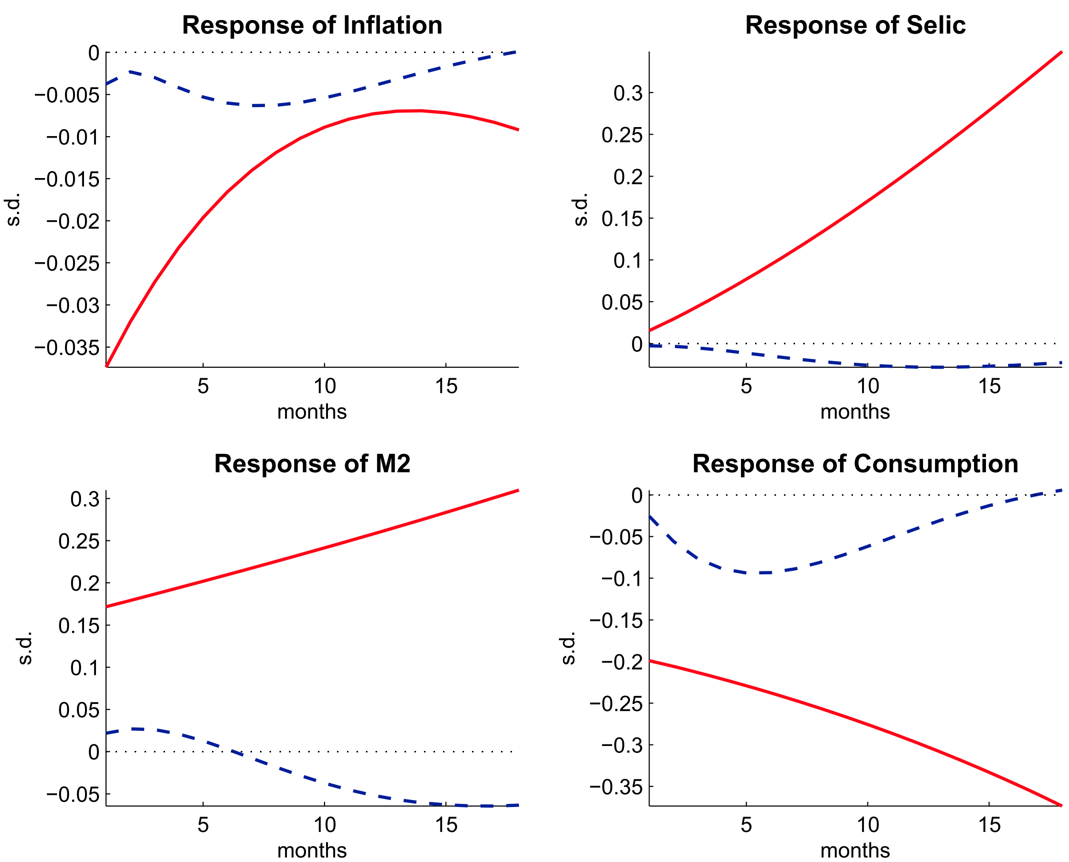

Fig. 5. Effect of a shock in the BFSI.
Obs.: Regime 1 of stress (solid line) and regime 2 of normality (dashed line).

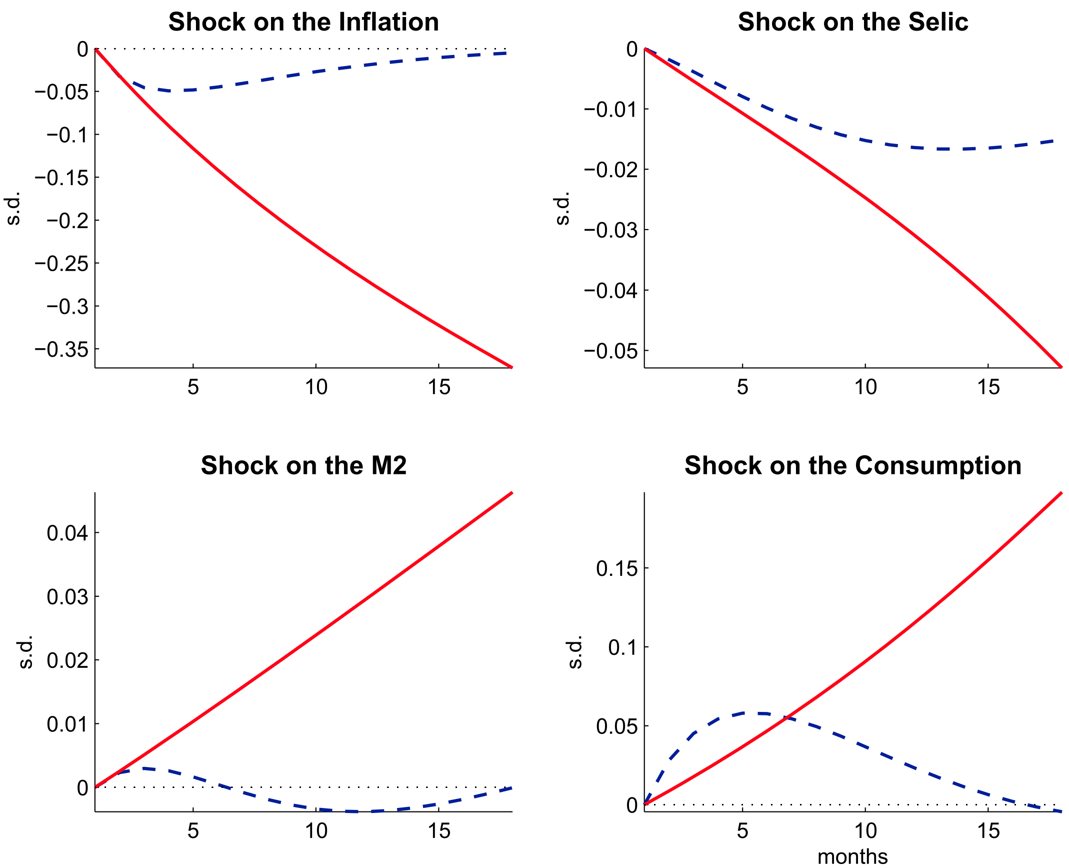

Fig. 6. Response of the BFSI to shocks.
Obs.: Regime 1 of stress (solid line) and regime 2 of normality (dotted line).

observed for the United States by Hubrich and Tetlow (2015); Mittnik and Semmler (2013); Davig and Hakkio (2010), for France by Aboura and Van Roye (2013), and even for other countries in the analysis of a global impact by Dovern and van Roye (2014). With this in mind, it is possible to anticipate one contribution of this work and to demonstrate that the effects of a shock of financial instability do not differ between developed and developing countries, such as Brazil, at least in terms of the economy's activity, represented here by household consumption. Thus, this finding further consolidates in the literature a greater indication of the effects of financial crisis on business cycles.

Regarding the effects during periods of stress, it should be noted that an increase in the BFSI index is related to an abrupt drop in economic activity and a decrease in inflation, and we can interpret that, in reaction, the monetary authority tends to increase the Selic interest rate. The negative effect on real activity, measured by consumer spending, proves more durable than the effect of the same shock during a period of stability, as well as producing an effect of longer duration for all variables. However, the tests do not allow us to establish a causal link between inflation, Selic, and M2 rates. The work of Ludvigson, Ma and Ng (2015) demonstrates that uncertainties in the financial market, measured here by the BFSI, are sources of these fluctuations. The authors believe that the drastic effects perceived in periods of stress are caused by financial stress and not the reverse. Brei and Buzaushina (2015), for instance, investigates how an emerging market economy is affected when it suddenly faces a higher risk premium and analyze theoretically the transmission mechanism using a small open economy model. They observe that a monetary authority which puts more weight on inflation stabilization increases the interest rate in response to a positive risk shock and households diminish their consumption level. As Brazil has adopted an Inflation Targeting Regime since 1999, we can interpret results within this framework.

On the other hand, Fig. 6 represents the effect of shocks on the other variables on the BFSI index. An increase in inflation, as explored in this analysis, has negative effects on stress. Even in normal times, an increase in inflation is transmitted to the financial market as a negative issue, pushing down index. This can be interpreted as a feeling of credibility in the inflation-targeting system, since the market does not seem to perceive deviations as a hazard. Yet, the effects of an increase in the Selic interest rate behave similarly in both moments. In normal times, the market responds positively with a small decrease in the BFSI. We expected that in normal times, a surprise increase in the federal interest rates could also boost financial stress, due to decreasing investment levels in response to

Table 1
Estimation results.

Regime	1c1v	2c2v	2c2v	1c2v	2c1v
Specification	Standard	Standard	Standard	Standard	Standard
Prior Duration		2.5	24	24	24
WZ MDD (log)	−109.93	−6.68	−2.66	−9.69	−32.15
Bridge MDD (log)		−97.37	−108.14	−16.29	−94.72
Regime	**1c1v**	**1c1v**	**2c2v**	**2c2v**	**2c2v**
Specification	AO	IP	AO	IP	AOIP
Prior Duration			24	24	24
WZ MDD (log)	−109.93	58.85	−2.17	199.71	196.38
Bridge MDD (log)			−118.63	98.98	104.38

Note: Marginal data density (MDD) computed with Waggoner and Zha (2012, WZ MDD) and Meng and Wong (1996, Bridge MDD) methods.

shrinkage of credit in the banking system[20]. However, the Brazilian experience of uncontrolled inflation in the 1980s and early 1990s can be the source of such behavior concerning financial stress. This can also be related to the Inflation Targeting Regime and the monetary authority commitment to ensuring stable prices.

We demonstrate that to adopt a contractionary monetary policy in a stressful moment would have a significant effect on the reduction of the market stress. In the same sense, in their counterfactual experiment, Hubrich and Tetlow (2015) identified that a decrease in the interest rate by the American government in October 2007, during a regime of instability, would have had a positive effect on the stress, causing a worsening in the scenario, as presented here. Thus, they interpreted that it demonstrates that in high-stress situations, agents regard conventional policy actions that would normally be beneficial as a confirmation of incipient financial difficulties.

For the effects of an increase in money growth, we can observe opposite effects on the BFSI in regimes of stress and normality. The model shows that an increase in the M2 monetary aggregate tends to have a slightly positive but non-significant increase in the first six months and then a negative effect on the financial market, which dissipates in 18 months. Once more, bearing this fact in mind, a government that ignores the existence of two regimes will deepen instability if it tries to calm the market with this type of mechanism. As is visible in the regime of stress, the effect is contrary and brings greater insecurity to the market. In addition, as already indicated, the shock exert a stronger effect and demonstrate the necessary care needed for any action taken in states of high stress.

Finally, we need to analyze the effects of an increase in household consumption. This result is an exception in the literature, as it is found only in Spain in the work of Mittnik and Semmler (2013), while in the United States, France, Germany, Italy, and the United Kingdom, the result was the opposite, differing only in magnitude (Aboura & Van Roye, 2013; Hubrich & Tetlow, 2015; Mittnik & Semmler, 2013). Despite the unexpected outcome, such a result can direct new studies in this sense, as it has at this point been noted in two countries (Brazil and Spain). Furthermore, we could argue that Brazil, as an emerging market, is subject to speculative capital flows, and investors could realize a profit opportunity during higher activity periods. We must not forget that the Brazilian economy has been performing with inconstant results, and periods of positive activity tend not to last long. Also, investors could believe that with an upsurge in the economy, the government may remove stimuli to strategic sectors, leading to a new period of low activity, which is an additional reason that higher stress in the market may be led by an increase in household consumption. We conduct a robustness check in the next subsection to verify if this result persists.

In addition to consolidating the connection between the financial sector and the real economy, these results measured how sensitive monetary policy is in periods of crisis. There is an indication that in periods of stress, agents respond differently to state interventions in the economy, as can be highlighted in the BFSI's response to shocks in the Selic rate and M2 offers. The instability reverses the effect of this policy, demonstrating the challenge of using conventional monetary policies in unstable economic periods. Thus, the actions adopted during crisis cannot be assessed the same way as in moments of normality in the financial market. We highlight that these are empirical results that represent the economic dynamics concerning shocks on macroeconomic aggregates and we cannot determine which is the optimal policy for a scenario of financial stress. In order to do this, a theoretical model for a small open country would have had to be designed, and this is beyond our main goal in this paper.

4.3. Robustness

For a robustness check, we compute three alternative specifications to verify if impulse responses persist (Table 1). We also compare models with the same data, but different regime structures and a prior belief of an average duration of staying in the same regime. Alternative specifications consider (i) Industrial Production instead of Consumption (IP); (ii) an alternative ordering of variables (AO); and (iii) an alternative ordering with industrial production instead of Consumption (AOIP). For the alternative ordering, we reorder variables such as $y_t = [\text{BFSI C INF M S}]'$. In this alternative ordering, we follow Basu and Bundick (2017), assuming that uncertainty shocks can have an immediate impact on consumption and the other variables, but non-uncertainty shocks do not affect the implied financial market instability on impact.

Further checks were made in order to verify if the two regimes for both coefficients and variance specification better fit the data. For

[20] As observed by Hubrich and Tetlow (2015) and Dahlhaus (2017) to the US.

this reason, we estimate a BVAR without regime changes, regime change only in the coefficients (2c1v) and only in the variation (1c2v). We also follow Sims et al. (2008) concerning the prior belief that the average duration of staying in the same regime is six quarters (24 months). In a previous version of this paper, we use a 2.5 months prior, following Davig and Hakkio (2010) and the average duration of financial stress regime in our first estimation. However, as Hubrich and Tetlow (2015) argue, this prior is consistent with the notion that shifts are associated with jumps in asset prices. Furthermore, goodness of fit of the data advocates in favor of the 24 months prior.

To evaluate models in terms of goodness of fit, an usual practice in this literature, the marginal data densities (MDDs) of candidate specifications are compared, using the method developed by Waggoner and Zha (2012) for computing (WZ mdd).[21] Thus, we observed that the model with 24 months prior achieved a higher log MDD than the specification with 2.5 months. All results in the paper consider these results.

Considering the results presented in Table 1, models with constant coefficients and variance perform worse than their counterparts with regime switching. Even though we cannot compare the MDD of models with different data inputs, specifications with regime change present better data fitting. It follows that the transmission of stress is properly thought of as a nonlinear phenomenon not only in developed countries, such as the US, but also in emerging countries, such as Brazil. Furthermore, for all of the specifications presented in Table 1, impulse response results persist, including the positive response of financial stress to an increase in the consumption (or industrial production).

5. Conclusion

This study has built an index of Brazilian Financial Stress Index (BFSI) with the aim of understanding the macro-financial linkages in periods of stress. The BFSI was able to capture expectations of and threats to the Brazilian financial market. Then, to understand the relationship between financial stress and the dynamics of the economy, the study used a Markovian switching vector auto-regressive model developed by Sims et al. (2008), estimated with a Bayesian approach.

The BFSI has demonstrated that it is capable of identifying historical periods of higher risk perception. The need to measure the conditions of the financial system has encouraged the creation of various indexes of financial instability around the world. In Brazil, however, this area of study is still in development. Also, given the fact that this literature branch as a whole has not yet been consolidated, there is no consensus on which variables should incorporate this index. Given the fact that the literature has not yet been consolidated, there is no consensus on the variables that should incorporate this index; thus, following some indexes in the literature, this study's first contribution is to develop a FSI for Brazil.

A possibility to advance the Brazilian financial stress index would be to adjust the model for a high frequency format with daily or weekly results. In addition, the model's factors are fixed, allowing an alternative to estimating the behavior of these factors in time, identifying the importance of each variable that moves the BFSI in a particular period. Still, it may be worthwhile to investigate whether the BFSI has the characteristics of a leading indicator for recessions in Brazil.

After the BFSI formulation, we estimate a MS-VAR with its application together with household consumption, money growth, and the Selic federal interest rate. This framework was able to identify the importance of the financial market to the Brazilian economy. The relevance of this relationship has become more evident only in the recent literature, with the understanding that financial cycles interact with business cycles and that financial crises tend to point to the end of growth periods, in addition to making the recessions in business cycles more profound.

Moreover, we observe a distinct behavior of the economy in periods of financial stress and stability, emphasizing that traditional monetary policies do not appear to be the most efficient in the face of financial crisis. Results demonstrate the need to expand empirical studies in this direction in search of more appropriate policies to address crises. Such periods, despite being moments of exception, need to be deeply understood by policy makers, softening the damage to the real side of economy, since stronger effects were observed during financial instability. Furthermore, the majority of studies that investigate the effects of economic policies during periods of financial shock shed light on developed countries. Confronted with this, we took a step forward by investigating an emerging market.

In periods of instability in comparison with normal periods, financial shocks have greater effects on the real economy and inflation. Still, despite the fact that it is a developing economy, major results for the Brazilian case do not differ from existing results in the literature for developed countries. Even though the response of BFSI to a positive shock on the interest rate in non-financial stress regimes differs from theoretical expectations and international literature, they are consistent with Brazilian monetary authority behavior. On the other hand, the effects of federal interest rates in financial stress regimes are consistent with the literature. This paper presents empirical evidences of state dependent patterns of economic dynamics during moments of financial stress, highlighting the importance of theoretical models capable of understanding optimal policies during such periods. Finally, it demonstrates that appropriate policies for some countries in normal times, such as an expansionary monetary policy, can worsen the scenario in an adverse situation, serving as an alert for the formulators of economic policies in Brazil.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.iref.2018.02.006.

[21] Table 1 also reports the log-MDD computed with the bridge method developed by Meng and Wong (1996), but all analyses are based on WZ mdd (log) results.

A. Data groups

Table A1
Risk Group Data

Code	value	Freq	Source	Begin	End
swapdi	Spread 1 × 120 months	D(5)	BM&F	02/01/2006	05/06/2015
ouro	Gold BM&F (log-return)	D(5)	BM&F	16/08/2002	30/04/2015
dl_ibov	Ibovespa (log-return)	D(5)	BM&F	03/01/2000	13/04/2015
v_ibov	log-return ibov vol.	D(5)	Economática, ARMA/GARCH	04/01/2000	13/04/2015
b_corp	Beta corporative sector	D(5)	Economática, Kalman Filter	03/01/2000	15/04/2015
v_cambio	exchange rate volatility	D(5)	BCB, ARMA/GARCH	03/01/2000	29/04/2015

Table A2
Bank Group Data

Code	value	Freq	Source	Begin	End
bfin	Total Finan/Assets	M	BCB	01/02/2000	01/01/2015
srisco	Spread risk operations	M	BCB	01/03/2000	01/01/2015
vol_banc	Bank sector volatility	D(5)	Economática, ARMA/GARCH	04/01/2000	13/04/2015
b_banc	Beta bank sector	D(5)	Kalman Filter	04/01/2000	13/04/2015

Table A3
External Group Data

Code	value	Freq	Source	Begin	End
credit	Cross-border claims (yoy)	Q	BIS	30/06/2000	30/09/2014
yield	Yield Spread (120 × 1 months)	D(5)	FED	03/01/2000	02/09/2015
vix	VIX S&P 500 Volatility Index	D(5)	CBOE	03/01/2000	11/09/2015
ted	TED Spread	D(5)	FRED	04/01/2000	04/09/2015
nqem	NASDAQ Emerging Markets Index (NQEM)	D(5)	NASDAQ	02/04/2001	11/09/2015
nqdm	NASDAQ Developed Markets Index (NQDM)	D(5)	NASDAQ	02/04/2001	11/09/2015

B. Hyperparameters priors

Priors selection for the Bayesian estimation follows Sims et al. (2008) recommendation for monthly frequency data and were also used by Davig and Hakkio (2010); Aboura and Van Roye (2013) and Hubrich and Tetlow (2015). From equation (5), which shows Sims et al. (2008) MSVAR model, priors are applied to $A(s_t)$ for all s_t and i variables, j equations and l lags. All parameters are presented in the Table B1.

Table B1
Priors selection for hyperparameters

Type of Prior	Value
Overall tightness for random walk prior	0.57
Relative tightness for the random walk prior on lag coefficients	0.13
Relative tightness for the constant term	0.10
Tightness on lag decay	1.20
Weight on nvars sums of coefficients dummy observations	10
Weight on single dummy initial observation including constant	10

References

Aboura, S., & Van Roye, B. (2013). *Financial stress and economic dynamics: An application to France*. Discussion Paper n. 1834. Kiel Institute for the World Economy.
Aikman, D., Haldane, A. G., & Nelson, B. D. (2015). Curbing the credit cycle. *The Economic Journal, 125*(585), 1072–1109.
Apostolakis, G. (2016). Spreading crisis: Evidence of financial stress spillovers in the Asian financial markets. *International Review of Economics & Finance, 43*, 542–551.
Apostolakis, G., & Papadopoulos, A. P. (2014). Financial stress spillovers in advanced economies. *Journal of International Financial Markets, Institutions and Money, 32*(C), 128–149.
Aruoba, S. B., & Diebold, F. X. (2010). Real-time macroeconomic Monitoring: Real activity, inflation, and interactions. *American Economic Review, 100*(2), 20–24.
Aruoba, S. B., Diebold, F. X., & Scotti, C. (2009). Real-time measurement of business conditions. *Journal of Business & Economic Statistics, 27*(4), 417–427.
Barndorff-Nielsen, O. E. (1997). Normal inverse Gaussian distributions and stochastic volatility modelling. *Scandinavian Journal of Statistics, 24*(1), 1–13.
Basu, S., & Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica, 85*(3), 937–958.
Baum, C. F., Caglayan, M., & Talavera, O. (2010). On the sensitivity of firms' investment to cash flow and uncertainty. *Oxford Economic Papers, 62*(2), 286–306.
Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking and Finance, 34*(8), 1886–1898.
BCB. (2002). *Relatório de Estabilidade Financeira*. v.1, n.1. Banco Central do Brasil.
BCB. (2008). *Relatório de Estabilidade Financeira*. v.7, n.2. Brsília, DF: Banco Central do Brasil.
BCB. (2009). *Relatório de Estabilidade Financeira*. v.8, n.1. Brsília, DF: Banco Central do Brasil.
Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *Quarterly Journal of Economics, 98*(1), 85–106.
Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. In J. B. Taylor, & M. Woodford (Eds.), *Handbook of macroeconomics* (1st ed., Vol. 1, pp. 1341–1393). Elsevier. chap. 21.
Bloom, N., Bond, S., & Van Reenen, J. (2007). Uncertainty and investment dynamics. *The Review of Economic Studies, 74*(2), 391–415.
Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307–327.
Bollerslev, T. (2010). Glossary to arch (GARCH). In T. Bollerslev, J. Russell, & M. Watson (Eds.), *Volatility and time series econometrics: Essays in honor of robert Engle*. Oxford University Press.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance, 45*, 182–198.
Brave, S. A., & Butters, R. A. (2011). Monitoring financial stability: A financial conditions index approach. *Economic Perspectives, 35*(1), 22.
Brave, S. A., & Butters, R. A. (2012). Diagnosing the financial System: Financial conditions and financial stress. *International Journal of Central Banking, 8*(2), 191–239.
Brei, M., & Buzaushina, A. (2015). International financial shocks in emerging markets. *Journal of International Money and Finance, 58*, 51–74.
Choudhry, T., & Wu, H. (2008). Forecasting ability of GARCH vs Kalman filter method: Evidence from daily UK time-varying beta. *Journal of Forecasting, 27*(8), 670–689.
Christiano, L., Ilut, C. L., Motto, R., & Rostagno, M. (2010). *Monetary policy and stock market booms*. National Bureau of Economic Research. Working Paper Series, No. 16402.
Claessens, S., Kose, M. A., & Terrones, M. E. (2012). How do business and financial cycles interact? *Journal of International Economics, 87*(1), 178–190 (Symposium on the Global Dimensions of the Financial Crisis).
Dahlhaus, T. (2017). Conventional monetary policy transmission during financial Crises: An empirical analysis. *Journal of Applied Econometrics, 32*(2), 401–421. jae.2524.
Davig, T., & Hakkio, C. (2010). What is the effect of financial stress on economic activity. *Economic Review, Q II*, 35–62.
Ding, Z., Granger, C. W., & Engle, R. F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance, 1*(1), 83–106.
Dovern, J., & van Roye, B. (2014). International transmission and business-cycle effects of financial stress. *Journal of Financial Stability, 13*, 1–17.
Drehmann, M., Borio, C., & Tsatsaronis, K. (2012). *Characterising the financial cycle: don't lose sight of the medium term!*.
Durbin, J., & Koopman, S. J. (2001). *Time series analysis by state space methods*. Oxford statistical science series. Oxford University Press.
Espinoza, R., Fornari, F., & Lombardi, M. J. (2012). The Role of Financial Variables in predicting economic activity. *Journal of Forecasting, 31*(1), 15–46.
Ferreira, J. T. A. S., & Steel, M. F. J. (2006). A constructive representation of univariate skewed distributions. *Journal of the American Statistical Association, 101*(474), 823–829.
Ghalanos, A. (2014). *rugarch: Univariate GARCH models.R package version 1.3-4*.
Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779–1801.
Hakkio, C. S., & Keeton, W. R. (2009). Financial stress: What is it, how can it be measured, and why does it matter? *Economic Review, 94*(2), 5–50.
Harvey, A. C. (1989). *Forecasting, structural time series models and the Kalman filter*. Cambridge University Press.
Holmes, E. E., Ward, E. J., & Wills, K. (2012). Marss: Multivariate autoregressive state-space models for analyzing time-series data. *The R Journal, 4*(1), 11–19.
Hubrich, K., & Tetlow, R. J. (2015). Financial stress and economic dynamics: The transmission of crises. *Journal of Monetary Economics, 70*, 100–115.
Kliesen, K. L., Owyang, M. T., & Vermann, E. K. (2012). Disentangling diverse measures: A survey of financial stress indexes. *Review, Sep*, 369–398.
Kliesen, Kevin L., & Smith, Douglas C. (2010). *Measuring financial market stress*. Economic Synopses. Federal Reserve Bank of St. Louis.
Lee, G. G. J., & Engle, R. F. (1993). A permanent and transitory component model of stock return volatility. In *Cointegration causality and forecasting a festschrift in honor of clive WJ granger* (pp. 475–497). Oxford: Oxford University Press.
Ludvigson, S. C., Ma, S., & Ng, S. (2015). *Uncertainty and business Cycles: Exogenous impulse or endogenous response?*. Working Paper 21803. National Bureau of Economic Research.
Meng, X.-L., & Wong, W. H. (1996). Simulating ratios of normalizing constants via a simple identity: A theoretical exploration. *Statistica Sinica, 6*(4), 831–860.
Mergner, S. (2009). *Applications of state space models in Finance: An empirical analysis of the time-varying relationship between macroeconomics*. Fundamentals and Pan-European Industry Portfolios. Univ.-Verlag Göttingen.
Mittnik, S., & Semmler, W. (2013). The real consequences of financial stress. *Journal of Economic Dynamics and Control, 37*(8), 1479–1499 (Rethinking Economic Policies in a Landscape of Heterogeneous Agents).
Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347–370.
Pitterle, I., Haufler, F., & Hong, P. (2015). Assessing emerging markets' vulnerability to financial crisis. *Journal of Policy Modeling, 37*(3), 484–500. When Will the Crisis End in the Eurozone and Emerging Markets?In Memory of Ronald I. McKinnon.
Rigobon, R., & Sack, B. (2003). Measuring the reaction of monetary policy to the stock market. *Quarterly Journal of Economics, 118*(2), 639–669.
Sims, C. A., Waggoner, D. F., & Zha, T. (2008). Methods for inference in large multiple-equation Markov-switching models. *Journal of Econometrics, 146*(2), 255–274.
Stock, J. H., & Watson, M. W. (2011). Dynamic factor models. In M. P. Clements, & D. F. Hendry (Eds.), *The oxford handbook of economic forecasting*. Oxford University Press.
Stona, F., Amann, J. C., Morais, M., Triches, D., & de Morais, I. A. C. (2015). Análise da estrutura a termo das taxas de juros em países América Latina entre 2006 a 2014. *RBFin: Brazilian Review of Finance, 13*(4), 650–690.
Waggoner, D. F., & Zha, T. (2012). Confronting model misspecification in macroeconomics. *Journal of Econometrics, 171*(2), 167–184 (Bayesian Models, Methods and Applications).
Zakoian, J.-M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and Control, 18*(5), 931–955.