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Financial Conditions Indicators for Brazil

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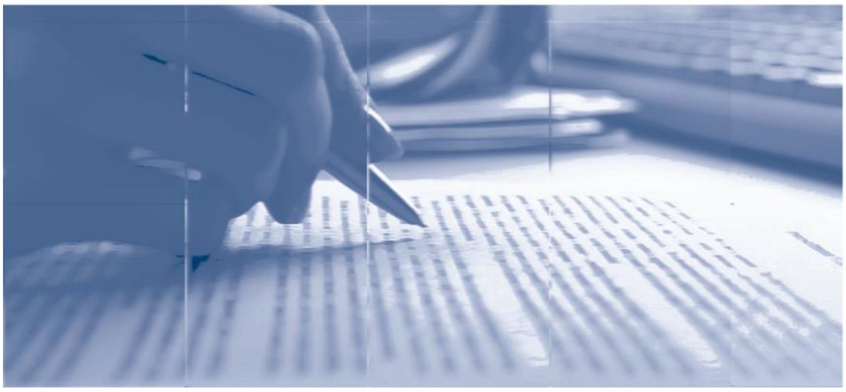

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Financial Conditions Indicators for Brazil

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Abstract

The Working Papers should not be reported as representing the views of the Banco Central do Brasil. The views expressed in the papers are those of the author(s) and do not necessarily reflect those of the Banco Central do Brasil.

In this paper, we propose a methodology to construct a Financial Conditions Indicator (FCI) based on Brave and Butters (2011) and Aramonte et al. (2013). The main idea is to use a selected set of economic and financial time series and aggregate their information content into a single index that summarizes the overall financial conditions of the economy. This approach can be further employed to forecast economic activity. An empirical exercise for Brazil is provided to illustrate the methodology, in which a modified IS-type equation (substituting the interest rate by the FCI) is employed to point forecast the output gap. In addition, a standard quantile regression technique (e.g. Koenker, 2005) is used to construct density forecasts and generate fan charts of future economic activity. A risk analysis is conducted within this setup in order to compute conditional probabilities of the output growth to be above/below a given scenario.

Keywords: Financial Condition Index, Forecasting Economic Activity.

JEL codes: C53, E32, G10, G17.

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1 Introduction

Financial conditions have an important influence on business cycles, reflecting not only the current economic situation, but also the market expectations on the future state of the economy. The response of real economic activity to the subprime crisis after 2008 has shown just how serious and harmful the impact of stress in financial markets on the economic activity can be. Thus, real-time assessment of financial conditions on an ongoing basis has become a critical issue for policymakers, regulators, financial market participants and researchers.

The financial conditions can be defined as the current state of financial variables that influence economic behavior and (thereby) the future state of the economy. In theory, such financial variables may include anything that characterizes the supply or demand of financial instruments relevant for economic activity. This list might comprise a wide array of asset prices and quantities (both stocks and flows), as well as indicators of potential asset supply and demand. The latter may range, for instance, from surveys of credit availability to the capital adequacy of financial intermediaries.

The vast literature on the monetary transmission mechanism is a natural starting place for understanding financial conditions. In that literature, monetary policy influences the economy by altering the financial conditions that affect economic behavior. The structure of the financial system is a key determinant of the importance of various channels of shocks' transmissions. For example, the large corporate bond market in the United States and its broadening over time suggests that market prices for credit are more powerful influences on U.S. economic activity than would be the case in Japan or Germany nowadays (or in the United States some decades ago). The state of the economy also matters for the overall stance of financial conditions: For example, financial conditions that influence investment may be less important in periods of large excess capacity.

In this paper, we define a Financial Conditions Indicator (FCI) as an aggregate measure of financial conditions in the economy. This work aims to construct a FCI to Brazil.[1] The main idea is to build the FCI such that it embodies information

[1] Previous attempts in this vein are the works of Sales et al. (2012) and Pereira da Silva et al. (2012).

about several markets' conditions (e.g. credit market) from a variety of indicators to condense it into a single measure. This procedure of obtaining information from several different sources ends up providing some indication of financial conditions that can not be obtained directly, such as risk aversion. This way, a FCI summarizes the information about the future state of the economy contained in the current financial variables. Ideally, an FCI should measure financial shocks – exogenous shifts in financial conditions that influence (or otherwise predict) future economic activity.

True financial shocks should be distinguished from the endogenous reflection or embodiment in financial variables of past economic activity that itself predicts future activity. If the only information contained in financial variables about future economic activity were of this endogenous variety, there would be no reason to construct an FCI: Past economic activity itself would contain all the relevant predictive information for future economic activity. Indeed, a single measure of financial conditions is insufficient to summarize all the predictive content. This way, in order to deal with this challenge, we build several FCIs and show the results in a simple (but intuitive way) to represent the uncertainty surrounding the process of building an FCI.

On the other hand, FCIs are typically designed to measure whether the general financial conditions are too "loose" or "tight" by historical standards. Although the instrument set by monetary policymakers is typically an interest rate, monetary policy affects the economy through other asset prices besides those grounded on debt instruments. Thus, movements in these other asset prices are likely to play an important role in how monetary policy is conducted. As Friedman and Schwartz (1963) have emphasized, the period of near-zero short-term interest rates during the contraction phase of the Great Depression of 1928 was one of highly contractionary monetary policy, rather than the reverse. As a result, it is dangerous always to directly associate the easing (or tightening) of monetary policy with a fall (or a rise) in short-term nominal interest rates. Since information on the credit conditions for households and firms also have implications for investment, output and inflation, an FCI is useful to assess the implications for the real economy of financial market developments. Consequently, FCIs can be useful in forecasting economic activity, making them useful for policy makers, particularly in relation to the definition of monetary or fiscal policy.[2]

The importance to the real economy of a properly functioning financial system is highlighted by the results of extensive economic literature, which shows that restrictive monetary policy, mandatory capital requirements and restrictions on bank financing can reduce the credit supply.[3] The effect is stronger in the case of small banks with less liquid assets, affecting more directly small businesses dependent on bank loans.[4] The decrease in credit supply ultimately affect investment, stocks and the economy as a whole.[5]

After the 2008 subprime crisis, there was a proliferation of indexes that seek to act as a proxy for financial conditions.[6] Despite the wide variety of methodologies, we next summarize the five main characteristics of the FCIs:

(i) They are largely based on financial variables, including implied volatilities, Treasuries yields, spreads, commercial paper yields, stock returns and exchange rates;

(ii) FCIs may include a relatively small set of variables up to hundreds of variables;

(iii) These variables are often aggregated using a statistical method called principal component analysis (PCA)[7] or by a weighted sum;[8]

[2]See Kliesen et al. (2012) for a good discussion about financial stress index and financial conditions indicator.

[3]See Bernanke and Blinder (1992), Oliner and Rudebusch (1996), Kashyap et al. (1994), Peek and Rosengren (1997) and Paravisini (2008).

[4]See Gertler and Gilchrist (1994), Stein and Kashyap (2000), Khwaja and Mian (2008) and Chava and Purnanandam (2011).

[5]See Bernanke (1983), Kashyap et al. (1994), Peek and Rosengren (1997, 2000), Calomiris and Mason (2003) and Campello et al. (2010).

[6]See, for example, Gauthier et al. (2004), Illing and Liu (2006), Nelson and Perli (2007), Beaton et al. (2009), Hakkio and Keeton (2009), Hatzius et al. (2010), Brave and Butters (2011), Sandahl et al. (2011), Carlson et al. (2012), Gumata et al. (2012), Kara et al. (2012), Johansson and Bonthron (2013) and Aramonte et al. (2013).

[7]The benefit of PCA is its ability to determine the individual importance of a large number of indicators so that each one may receive the weight consistent with its historical importance in the fluctuations of the financial system. Indexes of this type have the advantage of capturing the interconnectedness of financial markets, a desirable feature, allowing an interpretation of the systemic importance of each indicator. The indicator is more correlated with their peers the higher the weight it receives. This allows the possibility that a small deterioration in a heavily weighted indicator can mean more for financial stability than a large deterioration in an lightweighted indicator. Nonetheless, the PCA method also has its limitations. For example, the choice of which financial indicators to include is limited by the availability of frequency data, as well as the size of the series for which data are available. For details of how to deal with some of these restrictions, see Stock and Watson (2002) and Brave and Butters (2011).

[8]In the case of the weighted sum, the weights are normally assigned subjectively by the authors, although some of the indexes use more sophisticated methods.

(iv) They are typically expressed in terms of z-scores;[9]

(v) Existing evidence is unclear about whether FCIs should be thought of as coincident or leading indicators.

In this study, we combine the methodologies of Brave and Butters (2011) and Aramonte et al. (2013) in building an FCI for Brazil. In this sense, we use a pre-selected set of financial series and aggregate those variables into a single index based on different methodologies. As a result, we generate eight different financial conditions indicators. A historical decomposition of the Brazilian financial conditions reveals the relative importance of groups of variables, used in the construction of the FCIs, along the 2005-2015 period.

A selected FCI is also compared to economic activity series, and to the credit-to-GDP gap, showing that the financial conditions indeed Granger-causes the economic gaps (the reverse causality is also supported by the data), which is an interesting result in line with a "feedback-effect" argument, in which shocks originated within the financial system impact the real economy, as well as the real economy affects the financial system. This statistical relationship is further explored in the construction of an econometric model used to generate density forecasts for economic activity based on lagged FCIs. As a result, we provide a tractable framework for risk analysis regarding future prospects of economic activity.

The next section details the methodology used for the construction of a group of FCIs for Brazil, explaining each step of its construction. Section 3 presents the FCIs and evaluates its properties. Section 4 concludes. Additional Charts and Tables are shown in the Appendix.

[9] An exception is the index of financial stress of Carlson et al. (2012), which is expressed in terms of probabilities.

2 Methodology

Brave and Butters (2011) construct a financial conditions index for the United States, based on three main groups of variables: (i) money markets; (ii) debt and equity markets; and (iii) banking system. According to the authors, the money markets category is made up mostly of interest rate spreads that form the basis of most other financial conditions indexes; which are further complemented by measures of implied volatility and trading volumes of selected financial products.

The second group (debt and equity markets) includes equity and bond price measures (focused on volatility and risk premiums) as well as residential and commercial real estate prices, municipal and corporate bond, stock, asset-backed security, and credit derivative market volumes. Brave and Butters argue that the latter measures capture elements of both market liquidity and leverage, and that (in general) the indicators in this second category follow the same pattern as the first category, such that widening credit spreads, increasing volatility, and declining volumes, all denoting tighter debt and equity market conditions.

The third group (banking system) is formed essentially by survey-based measures of credit availability and accounting-based measures for commercial banks (and shadow banks), besides a few interest rate spreads. The authors highlight that the former indicators are basically measures of liquidity and leverage, although they could also capture risks related to deteriorations in credit quality.

On the other hand, Aramonte et al. (2013) investigate predictive ability of financial conditions indexes for the U.S. in respect to stock returns and macroeconomic variables. Again, financial conditions indexes are based on a variety of constituent variables and aggregation methods (see also Table 1 of Čihák et al., 2013).

In this paper, we focus on the both approaches of Brave and Butters (2011) and Aramonte et al. (2013) to form a group of macroeconomic/financial time series, which are used to construct a set of financial conditions indicators (FCIs) for Brazil.

2.1 Data

Brazil is in the ongoing process of developing a well-functioning financial system[10], with many challenges regarding financial development, capital market deepening and long-term investment finance. In fact, the Brazilian financial system can be characterized (among others) by the following features (see Pereira da Silva et al. (2012) and IMF-FSSA (2012) for further details):

- Credit-to-GDP ratio is relatively low in respect to international standards (despite the rapid credit growth of recent years);[11]

- Real estate credit market has been one of the most dynamic sectors of Brazilian credit market in recent years (although still representing a small share of total credit);

- Exposure to risks from the corporate sector (and the derivatives market) is much lower in comparison to developed countries;

- In respect to financial deepening,[12] *Brazil contributed with only 1.63% to global financial depth in 2009, in sharp contrast to the U.S. (29.28%), United Kingdom (7.73%) or China (7.13%);*

- Relatively small share of foreign banks presence;

- Financial system geared toward the domestic market (and its process of internationalization is recent and affects only a very small number of large conglomerates);

- Presence of large public sector banks (i.e. state-owned banks) that are backed by the federal government;

- Banks' funding is mostly domestic through deposits and repos, and Brazilian conglomerates dispose of a large and diversified domestic funding base;

- The Brazilian system of payments and settlements exhibits high compliance with

[10] Which would be characterized (for instance) by a global supply of safe assets, liquid financial markets, sound legal institutions and adequate property rights.

[11] According to Pereira da Silva et al. (2012): *"...several factors contributed to a sustainable credit expansion in the last ten years: the above mentioned macroeconomic stability led to an increase in formal employment and real income. Together with institutional reforms, social and financial inclusion policies, among other factors, led to a steady decline of the average domestic credit spread (and of the sovereign debt risk premium, measured by the Embi+Br index). The absence of significant external shocks in the 2003-2007 period must also be taken into account to understand the growth of credit in recent years."*

[12] Summing all assets and liabilities (held against residents and nonresidents) as a share of GDP gives a measure of the weight of total financial claims and counterclaims of an economy – both at home and abroad. Financial depth as a share of global depth is given by each country's contribution weighted by its GDP. See IMF-GFSR (2012, Table 3.4) for further details.

international standards;

- Credit market vulnerable to sudden floods (and sudden stops) of capital flows, especially under conditions of volatility abroad.

In order to cover some of the key features of the Brazilian financial system, we selected (*ad hoc*) a set of 28 time series, which are listed in Table 1 (see the Appendix B for further details). It is worth mentioning that this set of variables, of course, should not be viewed as an exhaustive summary of the several and distinct segments that compose the financial system but, rather, as an illustrative set of series that can be used to generate policy indicators.

Table 1 - Selected variables

Groups of variables	Time Series
1– Opportunity cost	Selic (monetary policy rate), Swap Pré x DI 1year, Slope of the term structure of interest rates,
	Credit Default Swap (CDS) Brazil, Lending rate (average interest rate of nonearmarked new credit operations).
2 – Banking credit	Real growth rate of nonearmarked credit operations outstanding, Non-Performing Loan (NPL),
	Loan-to-Deposit ratio (LTD), Return on Equity (ROE), Regulatory Capital to Risk-Weighted Assets (Basel ratio).
3 – Monetary aggregates	Monetary base, Money supply - Demand deposits, M1, M2, M3, M4.
4 – Capital markets	Ibovespa, Dow Jones, Nasdaq, FTSE100, DAX, Nikkei225.
5 – Foreign sector	Real effective exchange rate index (REER, IPCA), FDI - Foreign direct investment (% of GDP),
	FPI - Foreign portfolio investment (% of GDP), Embi+BR, VIX, 10-Year US Treasury.

The dataset covers the period 2005-2015. The cutoff date is January 15th, 2016 and the raw data is used to generate monthly FCIs from January 2005 to December 2015 (132 observations). The data sources are the Banco Central do Brasil, Bloomberg, BM&FBovespa, Ipeadata and Yahoo!Finance.

Regarding series transformations, the interest rate series (Selic, Swap and lending rate) are all used in real terms (deflated by IPCA, which is the Brazilian consumer price index (CPI) adopted by the Inflation Targeting Regime). The slope of the term structure of interest rates is defined as the difference between the Swap rates for 5 years and 1 year. The series of group 3 (monetary aggregates) are all seasonally adjusted (X12 filter), deflated by IPCA, first-differenced and smoothed by a twelve-month moving average (the same moving average is also adopted in the FPI series).

2.2 Ragged-edge

The real-time dataset exhibits missing values at the end of the sample, in the context of the so-called "ragged-edge" problem (i.e. missing data at the end of the sample, for some series, due to the non-synchronicity of data releases). The solution adopted here to overcome this issue is to realign those series with missing observations at the end of the sample, which are shifted forward in order to generate a balanced dataset with the most recent information (cutoff date). Banbura et al. (2012, p.18) list several recent papers which follow this same type of solution.

In our case, we applied the following procedures to deal with the "ragged-edge" issue: (i) all series available in a daily basis (e.g. financial series) are averaged in the month t of the cutoff date; (ii) missing (endpoint) values for the IPCA and Selic rates are filled with consensus market expectations at the cutoff date (from the Focus survey, organized by Banco Central do Brasil); and (iii) the remaining series are shifted forward an amount of s months.[13]

2.3 Constructing the FCIs

Firstly, to eliminate location and scale effects in the dataset, a standard normalization is applied to all series in order to generate the so-called *z-scores*, which are simply time series with zero mean and unity variance. Next, a signal inversion is applied to a subset of normalized series, in order to make the dynamics of each variable, used in the construction of the FCI, consistent with the signal interpretation of the FCI.[14] Finally, the FCI is simply defined as a weighted average of (signal-corrected) *z-scores*.

This way, all the methodological discussion hereafter relies on the choice of appropriate weights. Among several possibilities, we adopt three routes: (i) equal weights; (ii) economic activity-driven weights; and (iii) weights based on Principal

[13] We adopt s=1 for for lending rate, real growth rate of nonearmarked credit operations outstanding, NPL, LTD, all series of group 3, REER, FDI and FPI; and s=3 for ROE and Basel ratio.

[14] Signal inversion is adopted in the following variables: Real growth rate of nonearmarked credit operations outstanding, LTD, ROE, Basel ratio, all series of groups 3 and 4, FDI and FPI. The idea is to construct the FCI such that increases on the indicator suggest worsening financial conditions, whereas, decreases on the FCI indicate improvements in the financial conditions.

Component Analysis (PCA).[15]

Equal weights are the first and natural approach to aggregate distinct variables into a single time series. In the context of forecast combination, equal weights usually deliver better results than using "optimal weights" constructed to outperform other combinations in the mean-squared error (MSE) sense. See Bates and Granger (1969), Palm and Zellner (1992) and Timmermann (2006) for more details. One caveat of such approach, however, is that the FCI will heavily depend on the selection of series that compose the dataset (and how well balanced is such dataset, regarding the key features, shocks and tendencies of the financial system).

In the second case, the economic activity-driven weights are designed to produce an indicator (FCI) that exhibit some correlation with respect to the domestic economic activity, measured here by two (monthly) proxies: industrial production and IBC-BR (Brazilian Economic Activity Index). Weights are, thus, estimated from a Vector Autoregression (VAR) model, based on the logarithm first difference ($\Delta \ln$) of the economic activity proxy (IBC-BR or industrial production) and the first principal component of each group listed on Table 1. Then, impulse-response functions (IRF) are constructed and the weights are given by the (normalized) twelve-month accumulated response of the economic activity proxy, given shocks in the remaining variables.[16]

Regarding the third route, weights are based on the PCA to summarize the *z-scores* into a single indicator. The idea is to extract the first and/or second principal components from a base set of variables. This way, the FCI is constructed by two competing approaches:

(a) single-step: the FCI is defined as the first principal component of the full set of 28 variables listed on Table 1. Alternatively, the FCI is defined as a weighted average of the first and second principal components of the same set of 28 variables,

[15] PCA consists of mathematically transforming an original set of variables into another set (of same dimension) variables called "principal components", independent of each other and estimated to retain, in order of estimation, the maximum amount of information in terms of total variation contained in the data. Each principal component is a linear combination of the original variables, and the first principal component retains the highest common variation of the data. See Johnson and Wichern (1992) for more details.

[16] We follow the "generalized impulse" methodology of Pesaran and Shin (1998) to construct the impulse-response functions (IRF), based on an orthogonal set of innovations that does not depend on the VAR ordering. See Appendix D for the constructed IRFs.

in which the weights are the respective eigenvalues;

(b) two-step: the first principal component is extracted from each one of the five groups of Table 1. Then, in the second step, the FCI is defined as the first principal component of the set of five first principal components (previously estimated) or, alternatively, based again on a weighted average (i.e. eigenvalues) of the first and second principal components extracted from the same set of five series (i.e. the first principal components estimated in the first step).

Table 2 summarizes all FCI candidates from the described methodologies.

Table 2 - Summary of the FCIs

Indicator	Base set of variables (number of variables)	Aggregation	Weighting scheme
FCI1	all variables (28)	-	equal weights
FCI2	all variables (28)	single step	PCA: 1st principal component
FCI3	all variables (28)	single step	PCA: weighted average of 1st and 2nd princ.compon.
FCI4	1st principal component of each group (5)	-	equal weights
FCI5	1st principal component of each group (5)	two steps	PCA: 1st principal component
FCI6	1st principal component of each group (5)	two steps	PCA: weighted average of 1st and 2nd princ.compon.
FCI7	1st principal component of each group (5)	VAR-based	economic activity-driven weights (IBC-BR)
FCI8	1st principal component of each group (5)	VAR-based	economic activity-driven weights (ind. prod.)

Table 3 presents the resulting weights used to construct the FCIs, which are generated from the different sets of variables, aggregation and weighting schemes. Notice that for all candidates (excepting FCI1) weights are not necessarily positive across the 28 base-variables, which is due to the PCA approach that generates weights (also known as "loadings") in the real line (and not restricted to the zero-one interval). See Appendix C for further details on the PCA results.

Nonetheless, in order to reveal the relative importance of each one of the 28 series, in respect to the FCI candidates, we also compute absolute weights and re-normalize the weighting vector for each FCI, as presented in Table 4.

Table 3 - Normalized Weights

Variables	FCI1	FCI2	FCI3	FCI4	FCI5	FCI6	FCI7	FCI8
Selic (policy interest rate)	0.036	0.567	0.221	0.062	1.718	0.034	0.060	0.054
Swap Pre x DI 1 year	0.036	0.536	0.209	0.061	1.699	0.033	0.059	0.054
Slope of the term structure	0.036	-0.118	-0.117	-0.055	-1.517	-0.030	-0.053	-0.048
Lending rate	0.036	0.047	0.140	0.060	1.660	0.032	0.058	0.052
CDS spread	0.036	-0.200	0.064	0.031	0.864	0.017	0.030	0.027
Real growth of credit outstanding	0.036	-0.726	-0.181	0.062	-3.889	0.201	0.063	0.042
NPL	0.036	0.409	0.042	-0.037	2.307	-0.119	-0.038	-0.025
LTD	0.036	0.821	0.188	-0.068	4.257	-0.220	-0.069	-0.046
ROE	0.036	-0.661	-0.185	0.058	-3.619	0.187	0.059	0.039
Basel ratio	0.036	-0.508	-0.115	0.044	-2.728	0.141	0.045	0.030
Monetary base	0.036	-0.582	-0.113	0.053	-2.860	0.194	0.038	0.034
Demand deposits	0.036	-0.566	-0.094	0.053	-2.824	0.192	0.038	0.033
M1	0.036	-0.585	-0.098	0.054	-2.909	0.198	0.039	0.034
M2	0.036	-0.551	-0.130	0.027	-1.471	0.100	0.020	0.017
M3	0.036	-0.682	-0.114	0.051	-2.742	0.186	0.037	0.032
M4	0.036	-0.679	-0.108	0.056	-2.971	0.202	0.040	0.035
Ibovespa	0.036	0.163	0.162	0.010	0.506	-0.026	0.009	0.009
Dow Jones	0.036	0.714	0.154	0.058	3.022	-0.157	0.054	0.057
Nasdaq	0.036	0.783	0.164	0.056	2.900	-0.151	0.051	0.054
FTSE100	0.036	0.493	0.123	0.055	2.853	-0.148	0.051	0.054
DAX	0.036	0.716	0.165	0.058	3.002	-0.156	0.053	0.056
Nikkei225	0.036	0.278	-0.004	0.045	2.353	-0.122	0.042	0.044
REER	0.036	-0.068	0.112	0.076	0.512	0.152	0.116	0.133
FDI	0.036	0.474	0.104	-0.016	-0.107	-0.032	-0.024	-0.028
FPI	0.036	0.084	0.082	0.062	0.416	0.124	0.095	0.108
Embi+BR	0.036	0.017	0.118	0.072	0.484	0.144	0.110	0.125
10-Year US Treasury	0.036	0.647	0.194	0.012	0.083	0.025	0.019	0.022
VIX	0.036	0.178	0.019	0.000	-0.001	0.000	0.000	0.000
Sum	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*	*1.000*

Table 4 - Relative importance (%) of each variable for the FCIs

Variables	FCI1	FCI2	FCI3	FCI4	FCI5	FCI6	FCI7	FCI8
Selic (policy interest rate)	3.6	4.4	6.3	4.6	3.1	1.0	4.4	4.2
Swap Pre x DI 1 year	3.6	4.2	5.9	4.5	3.0	1.0	4.3	4.1
Slope of the term structure	3.6	0.9	3.3	4.0	2.7	0.9	3.9	3.7
Lending rate	3.6	0.4	4.0	4.4	3.0	1.0	4.2	4.0
CDS spread	3.6	1.6	1.8	2.3	1.5	0.5	2.2	2.1
Real growth of credit outstanding	3.6	5.7	5.1	4.6	6.9	6.0	4.6	3.3
NPL	3.6	3.2	1.2	2.7	4.1	3.6	2.7	1.9
LTD	3.6	6.4	5.3	5.0	7.6	6.6	5.1	3.6
ROE	3.6	5.1	5.3	4.3	6.4	5.6	4.3	3.0
Basel ratio	3.6	4.0	3.3	3.2	4.8	4.2	3.3	2.3
Monetary base	3.6	4.5	3.2	4.0	5.1	5.9	2.8	2.6
Demand deposits	3.6	4.4	2.7	3.9	5.0	5.8	2.8	2.6
M1	3.6	4.6	2.8	4.0	5.2	6.0	2.8	2.7
M2	3.6	4.3	3.7	2.0	2.6	3.0	1.4	1.3
M3	3.6	5.3	3.2	3.8	4.9	5.6	2.7	2.5
M4	3.6	5.3	3.1	4.1	5.3	6.1	2.9	2.7
Ibovespa	3.6	1.3	4.6	0.7	0.9	0.8	0.7	0.7
Dow Jones	3.6	5.6	4.4	4.3	5.4	4.7	3.9	4.4
Nasdaq	3.6	6.1	4.7	4.1	5.2	4.5	3.8	4.2
FTSE100	3.6	3.8	3.5	4.1	5.1	4.5	3.7	4.1
DAX	3.6	5.6	4.7	4.3	5.3	4.7	3.9	4.4
Nikkei225	3.6	2.2	0.1	3.4	4.2	3.7	3.0	3.4
REER	3.6	0.5	3.2	5.6	0.9	4.6	8.5	10.2
FDI	3.6	3.7	3.0	1.2	0.2	1.0	1.8	2.1
FPI	3.6	0.7	2.3	4.6	0.7	3.7	6.9	8.3
Embi+BR	3.6	0.1	3.3	5.3	0.9	4.3	8.0	9.7
10-Year US Treasury	3.6	5.0	5.5	0.9	0.1	0.7	1.4	1.7
VIX	3.6	1.4	0.5	0.0	0.0	0.0	0.0	0.0
Sum	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*

The weights shown in Table 4 are aggregated by groups and presented in Table 5. Notice that, in general, the various groups provide a balanced amount of information to form each considered FCI. This aggregation serves as a final check for the existence of clusters of few variables that could potentially account for the majority of the FCI dynamics (which is a non-desirable feature in the FCI designing process).

Table 5 - Relative importance (%) of each group for the FCIs

Groups of variables	FCI1	FCI2	FCI3	FCI4	FCI5	FCI6	FCI7	FCI8
1 – Opportunity cost	17.9	11.4	21.3	19.9	13.3	4.4	19.0	18.2
2 – Banking credit	17.9	24.3	20.2	19.9	29.9	26.1	20.0	14.1
3 – Monetary aggregates	21.4	28.4	18.7	21.8	28.0	32.3	15.4	14.4
4 – Capital markets	21.4	24.5	21.9	20.9	26.0	22.9	19.0	21.2
5 – Foreign sector	21.4	11.4	17.9	17.6	2.8	14.3	26.6	32.1
Sum	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*	*100.0*

3 Results

Now, one can easily construct the FCIs according to the different methodologies, previously described, and the respective weights. In order to avoid scale effects in the comparison of FCIs, we apply a final normalization (zero mean and unity variance) on the indicators, constructed from weights shown in Table 3, and add 100 to the final series (for all observations).

This way, all FCIs will exhibit sample mean equal to 100 and standard deviation equal to one. Those periods in which the FCI is above the benchmark 100 level indicate worse financial conditions in Brazil (in respect to the sample period) and, reversely, periods such that the FCI is below the 100 level suggest (relatively) better financial conditions. The results are shown in Figures 1 and 2.

Figure 1 - Financial Conditions Indicators (FCIs) for Brazil

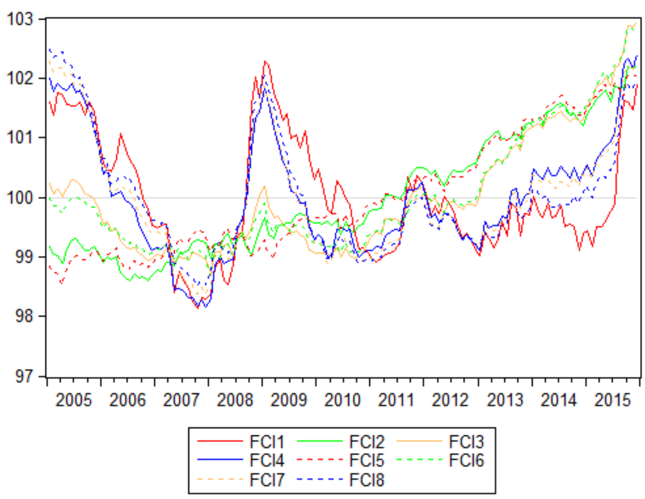
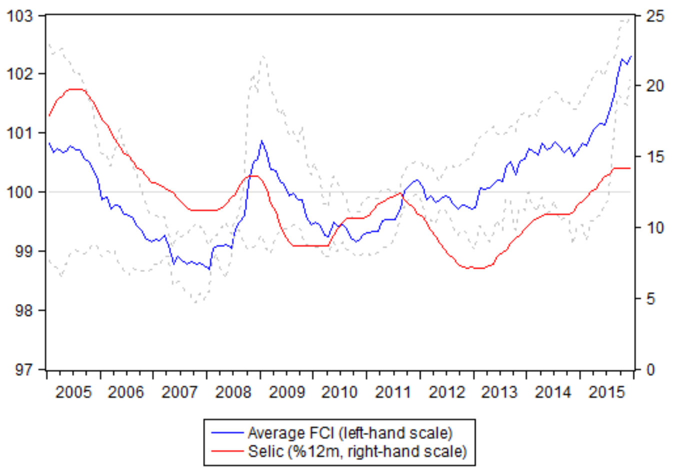


Figure 2 - Average, Maximum and Minimum FCI

and the monetary policy interest rate (Selic)

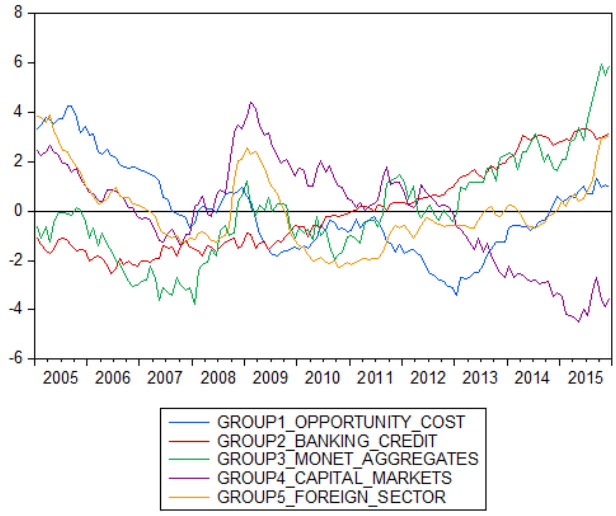


The dynamics of the FCI candidates reflect their different weights and aggregation schemes. For instance, FCI2 and FCI5 show an upward trend along the considered sample, whereas FCI1, FCI4 and FCI8, despite being more volatile, exhibit similar dynamics and are relatively more prone to explain crisis events. Indeed, the referred FCIs indicate worse financial conditions with the aftermath of the global crisis in 2008 (in comparison to the historical pattern observed along 2006 and 2007), followed by a recovery path by mid-2009. Later on, after a worsening trajectory observed along the second semester of 2011, these FCI candidates suggest some improvements in the financial conditions (along 2012 and the beginning of 2013), with reverse of this trend from the second quarter of 2013 until the last quarter of 2015.

Compared to the monetary policy interest rate (Selic), the average FCI exhibits a positive sample correlation of 0.28. This correlation jumps to 0.58, for Selic and FCI4 (and to 0.69, for Selic and FCI8), confirming that the policy rate is indeed a key series for the financial conditions, but does not account for the whole story. In other words, the FCI embodies a much broader information set, when compared to the interest rate series, containing information from distinct markets and different aspects of the economy and the financial system that the interest rate can not cover alone.

Now, in order to better understand the driving-forces behind the FCI dynamics, we depict in Figure 3, for illustrative purposes, the first principal component of each group of variables (formed by signal-corrected z-*scores*). See the Appendix B for a complete picture of the dataset, in which graphs for all variables (raw data) are presented.

Figure 3 - First principal component of each group of variables (signal-corrected z-*scores*)

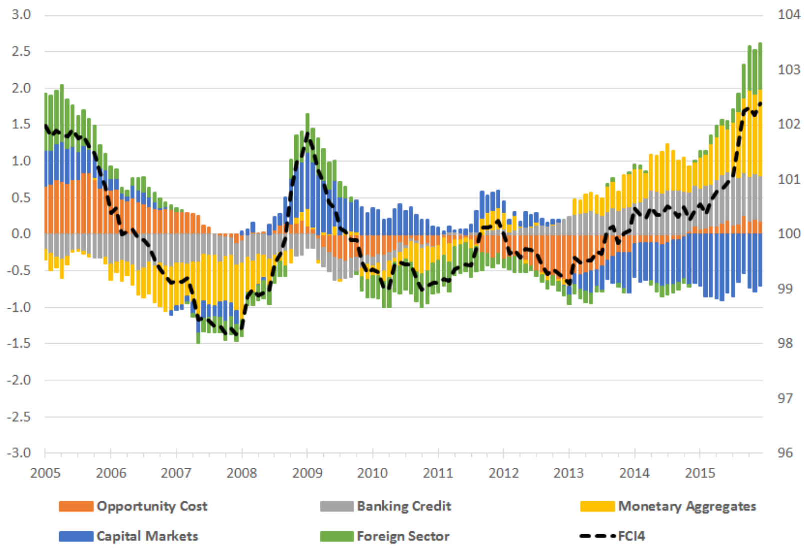


Regarding Group 1, notice the (overall) declining trend since 2005, essentially reflecting the decrease of the (nominal) monetary policy interest rate (Selic), which moved from 18.25 % p.a. (January 2005) to 10.00 % p.a. (December 2013). In respect to Group 2, the banking credit variables (in general) reacted to the global crisis towards a tightening-credit-conditions stance until the end of the sample. The Group 3 variables also reacted to the global crisis in 2008, by exhibiting easing financial conditions until 2010, followed by a reverse trend until 2015.

In turn, the capital market indexes (in general) experienced a 2005-2007 period of steady growth, followed by a sequence of significant drops (from the last quarter of 2007 until the beginning of 2009) also as a consequence of the global crisis. Nonetheless, this group of variables (excepting the Ibovespa index) present since 2009 an upward trend, in great part as a consequence of the quantitative easing programs adopted in many developed countries, thus, contributing to the improvement of the financial conditions indicators. Finally, the external sector (Group 5) exhibits similar dynamics (before and after the 2008 crisis), with a recent period (since 2014) of significant deterioration in the financial conditions, in great part due to the depreciation of the exchange rate, and increases of the 10-Year U.S. Treasury rate (and of the Embi+Br).

Figure 4 shows how the dynamics of each group of variables, summarized here by its first principal component, can affect the time evolution of the Brazilian financial conditions. In this sense, for illustrative purposes, we plot the magnitude of the first principal component of each group (stacked in each period) together with the FCI4. We choose FCI4 because it is an indicator that does not depend on economic activity proxies for its construction.

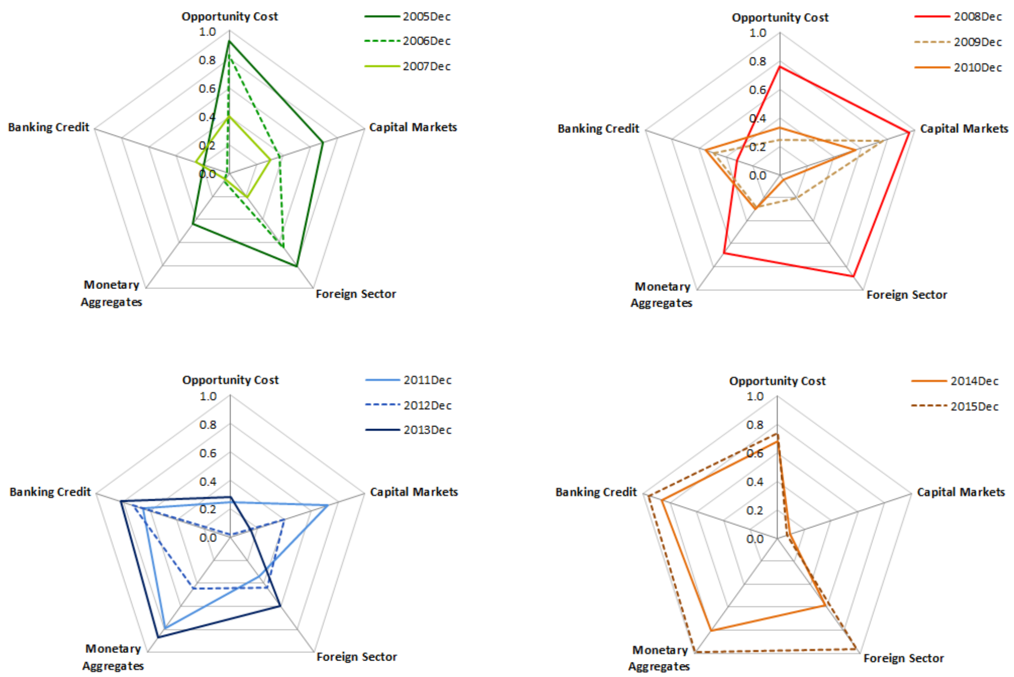
Figure 4 - FCI decomposition by group of variables



The results presented in Figures 3-4 can further be interpreted in terms of static comparisons. In other words, we can use the first principal component of each group to build a "map of contributions" to the financial conditions indicators at given points in time. To do so, we first compute the empirical (unconditional) sample quantiles of the referred first principal components, along the whole considered sample. Next, we select a few periods (i.e. December of each year) and calculate the respective quantile level which corresponds to (each) first principal component. Then, for a given point in time, we plot the quantile level of each group and compare it across the five groups of variables. One of the advantages of such approach is to deal with a normalized measure (which belongs to the zero-one interval) comparable across the distinct groups. The results are presented in Figure 5.

Note the "shrinking" evolution of the curves in the upper-left graph of Figure 5 (suggesting significant improvements in the financial conditions in the pre-crisis period until December 2007), which is a detailed view of the FCI dynamics depicted in Figure 1. On the upper-right graph notice that in December 2008 almost all groups were positioned in higher quantiles (excepting the banking credit variables), reflecting the relatively bad financial conditions stance, in respect to the historical pattern observed along the entire 2005-2015 sample.

Figure 5 - Map of group contributions

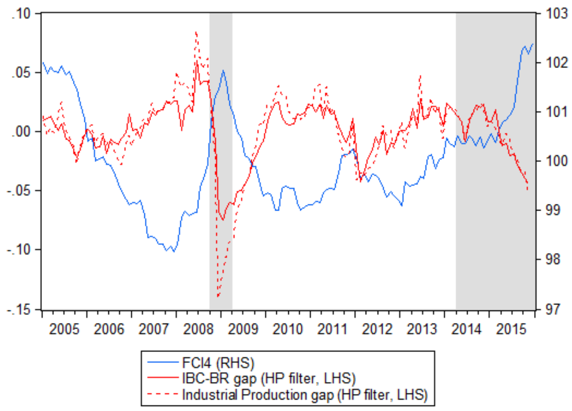


Moreover, regarding the last sample period (December 2015), note that the higher quantiles are occupied by groups 2, 3 and 5 (banking credit, monetary aggregates and foreign sector). In turn, group 1 (opportunity cost) moved since 2013 towards tighter financial conditions (among others, due to higher domestic and foreign interest rates). Finally, group 4 (capital markets) is the only group that contributes (at the last sample period) to a relatively loose financial stance, which is essentially due to the relatively good performance of foreign stock exchanges in the recent years.

3.1 Assessing the FCI

We now compare the FCI4 with the seasonally adjusted economic activity proxies. We also plot the recession periods according to the Brazilian Business Cycle Dating Committee (CODACE), which establishes reference chronologies for the Brazilian economic cycles (for further details see http://portalibre.fgv.br). In respect to the economic activity proxies (IBC-BR or industrial production), we plot the respective Hodrick-Prescott (HP) filtered gaps in order to remove non-stationary historical trends. The results are presented in Figure 6.

Figure 6 - FCI and Economic Activity



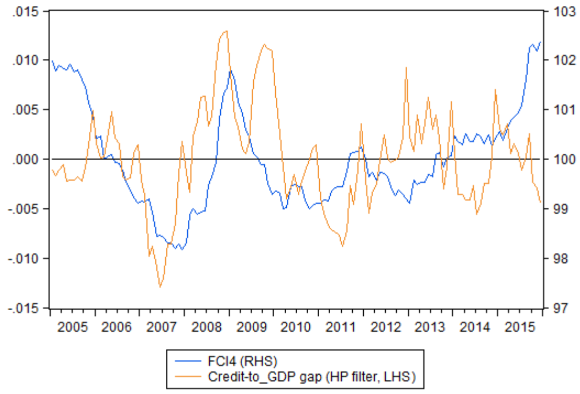
Note: Gray vertical bars display the recession periods

according to the most recent report of CODACE (August 2015).

It is worth mentioning that the 2008/2009 crisis imposed, firstly, a deterioration on the overall financial conditions (since the beginning of 2008) and, then, only several months later, the business cycles suffered the negative impact (by the end of 2008), whereas the FCI continued to increase until the first quarter of 2009. According to Borio (2011), empirical evidence suggests that financial and business cycles might not be synchronized (related, for instance, to a longer duration of the financial cycle in respect to the business cycle). Although we deal here with very few recession episodes, notice (from a visual inspection on Figure 6) that the increase of the FCI observed since the beginning of 2008 (as well as since 2013) seems to anticipate the recession periods (and, more broadly, economic activity drops) by several months.

On the other hand, financial development is often measured in the literature by the credit-to-GDP ratio (Borio, 2011). Figure 7 shows the FCI4 plotted together with a credit-to-GDP gap (leverage measure), computed from the total credit operations in the financial system (as a ratio to GDP) and the HP filtering.

Figure 7 - FCI and Credit-to-GDP gap



In order to look for contemporaneous (or lagged) common movements, we next calculate the sample correlations between the FCI4 and the considered economic (and credit) gaps.

Table 6 - Contemporaneous and lagged correlations

(leads and lags in months)

	IBC-BR Gap (t)	Ind. Prod. Gap (t)	Credit-to-GDP Gap (t)
FCI4 (t+6)	0.152	0.132	0.323
FCI4 (t+5)	0.080	0.056	0.342
FCI4 (t+4)	-0.014	-0.048	0.364
FCI4 (t+3)	-0.136	-0.170	0.382
FCI4 (t+2)	-0.273	-0.310	0.392
FCI4 (t+1)	-0.411	-0.440	0.374
FCI4 (t)	-0.515	-0.533	0.342
FCI4 (t-1)	-0.580	-0.590	0.296
FCI4 (t-2)	-0.614	-0.602	0.251
FCI4 (t-3)	-0.606	-0.569	0.214
FCI4 (t-4)	-0.576	-0.524	0.188
FCI4 (t-5)	-0.541	-0.470	0.167
FCI4 (t-6)	-0.479	-0.388	0.154

The negative signs obtained from correlations between the FCI and output gaps indicate that financial and business cycles are indeed not synchronized. One possible explanation would be the (possible) longer duration of financial cycles. It is also worth noting that the maximum absolute sample correlation (marked in yellow) between the FCI4 and the economic gaps are obtained for two (months) lags of

FCI4, whereas for the credit-to-GDP gap is computed from a two-month lead of FCI4. These results, although based on unconditional calculations, suggest that the selected financial conditions indicator (FCI4) might anticipate economic gap movements (and also could, potentially, be anticipated by a credit gap). Nonetheless, a more formal investigation to check these preliminary results is next provided based on Granger causality tests.[17]

Table 7 - Granger Causality test (p-values)

	Number of lags considered in the Granger Causality test						
Null hypothesis	**2**	**3**	**4**	**5**	**6**	**7**	**8**
FCI4 does not Granger Cause IBC_BR_GAP	0.000	0.001	0.002	0.005	0.003	0.008	0.005
FCI4 does not Granger Cause IND_PROD_GAP	0.000	0.000	0.001	0.002	0.001	0.001	0.002
FCI4 does not Granger Cause CREDIT_TO_GDP_GAP	0.927	0.893	0.935	0.988	0.994	0.987	0.983
CREDIT_TO_GDP_GAP does not Granger Cause FCI4	0.677	0.818	0.851	0.922	0.814	0.879	0.916
CREDIT_TO_GDP_GAP does not Granger Cause IBC_BR_GAP	0.203	0.247	0.387	0.524	0.555	0.582	0.610
CREDIT_TO_GDP_GAP does not Granger Cause IND_PROD_GAP	0.308	0.403	0.382	0.487	0.451	0.587	0.640
IBC_BR_GAP does not Granger Cause FCI4	0.000	0.001	0.011	0.016	0.036	0.050	0.066
IBC_BR_GAP does not Granger Cause IND_PROD_GAP	0.524	0.482	0.234	0.387	0.315	0.493	0.674
IBC_BR_GAP does not Granger Cause CREDIT_TO_GDP_GAP	0.506	0.352	0.422	0.226	0.327	0.222	0.275
IND_PROD_GAP does not Granger Cause FCI4	0.000	0.002	0.011	0.024	0.036	0.023	0.036
IND_PROD_GAP does not Granger Cause IBC_BR_GAP	0.339	0.276	0.369	0.494	0.599	0.742	0.815
IND_PROD_GAP does not Granger Cause CREDIT_TO_GDP_GAP	0.395	0.343	0.506	0.536	0.674	0.289	0.302

Firstly, note that FCI4 Granger-causes (GC) the economic gaps. Moreover, the GC tests also suggest the existence of causality in both directions, in line with a "feedback-effect" argument, in which shocks originated within the financial system impact the real economy, as well as the real economy affects the financial system.

On the other hand, the results indicate no Granger causality between FCI4 and the credit-to-GDP gap (in neither directions), despite the credit gap apparently anticipating the FCI4 movements along the 2007-2008 period, as shown in Figure 7. One explanation would be the relatively short time-span (11 years) to properly study the credit and financial cycles, which are often characterized in the literature by very low frequencies.

Now, we discuss whether (or not) the selected FCI is indeed informative about future innovations to economic activity in Brazil. Aramonte et al. (2013) evaluate

[17] Regarding the three considered gaps (IBC-BR, Industrial Production and Credit-to-GDP) the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests reject the null hypothesis of a unit root at a 1% significance level. Moreover, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test does not reject the null of stationarity (p-value above 10%). On the other hand, the ADF and PP tests for the FCI4 do not reject the null of a unit root (both p-values above 10%). However, the KPSS test also does not reject the null of stationarity for the FCI4 (p-value>10%).

the predictive ability of financial conditions indexes for stock returns and macroeconomic variables in the United States. To do so, the authors study a series of monthly and quarterly predictive regressions of the form:

$$y_t = \alpha + \beta FCI_{t-1} + \varepsilon_t, \quad (1)$$

where y_t is the dependent variable (stock returns or macro variables) and FCI_{t-1} is the one-period lagged FCI. The intercept α and the FCI coefficient β are estimated with OLS, and their statistical significance are assessed with either heteroskedasticity consistent standard errors (or with the local-to-unity asymptotics procedure of Campbell and Yogo, 2006).[18]

In our case, we study the multi-horizon step ahead predictive power of FCI in respect to our proxy for output gap y_t (based on IBC-BR or industrial production). Our predictive regression is the following:

$$y_t = \alpha + \beta_1 y_{t-h} + \beta_2 FCI_{t-h} + \beta_3 z_{t-h} + \varepsilon_t, \quad (2)$$

where h is the (monthly) forecast horizon, and the set of regressors now includes the lagged variable y_{t-h} (to account for some autoregressive dynamics) and a control variable z_{t-h}.

Firstly, notice that for $h > 1$ we take the "direct forecast approach", in contrast to the "recursive forecast" route (see Marcellino, Stock and Watson (2006) for a good discussion).[19]

Secondly, since we are dealing with a regression for the output gap, the previous equation takes the flavour of an IS curve, where the output gap (which summarizes the overall conditions of the aggregate demand) depends here on its own lagged value

[18] In fact, Aramonte et al. (2013) assume that FCI follows an AR(1) process, and use local-to-unity asymptotics (unless the autoregressive root of the FCI is sufficiently distant from one, as defined by the authors) or unless there is no correlation between the innovations to the FCI's autoregressive process and the innovations in the regression of the predicted variable on the FCI.

[19] According to the authors, "iterated" multi-period ahead time series forecasts are made using a one-period ahead model, iterated forward for the desired number of periods, whereas "direct" forecasts are made using a horizon-specific estimated model, where the dependent variable is the multi-period ahead value being forecasted. Which approach is better is an empirical matter: in theory, iterated forecasts are more efficient if correctly specified, but direct forecasts are more robust to model misspecification.

and also on the past financial conditions (instead of the lagged real interest rate, as often used in standard IS curve estimations). Regarding Brazilian data, it is also common to introduce as control variables some fiscal series and/or external shocks' proxies (see BCB (2011, p.378) for further details). Here, instead, we only consider a dummy variable to control for the 2008 crisis and its impact on the economic gaps (by the end of 2008). The estimation results for a set of monthly forecast horizons h are presented in Tables 8-9.[20]

Provided the Granger causality tests on Table 7 (for the FCI and the economic activity gaps) indicate causality in both directions, we also perform endogeneity tests to check for the need of using instrumental variable regressions (recall that if endogeneity is present, then, OLS estimates will be biased and inconsistent).[21]

Table 8 - Regression Estimates (IBC-BR)

Dependent Variable: IBC-BR gap (t)

Regressors	h=1	h=2	h=3	h=6	h=9	h=12
Constant	33.490	66.619	99.159	142.112	128.437	74.817
	(0)	(0)	(0.001)	(0)	(0.001)	(0.098)
IBC-BR gap (t-h)	0.823	0.687	0.497	-0.018	-0.344	-0.435
	(0)	(0)	(0)	(0.927)	(0.058)	(0)
FCI4 (t-h)	-0.335	-0.666	-0.992	-1.422	-1.285	-0.748
	(0)	(0)	(0.001)	(0)	(0.001)	(0.097)
Dummy 2008	-4.128	-5.897	-6.120	-5.186	-4.871	-4.177
	(0)	(0)	(0)	(0)	(0)	(0)
R-squared	0.824	0.712	0.573	0.324	0.253	0.198
Adjusted R-squared	0.820	0.705	0.563	0.307	0.234	0.177
Residual autocorrelation LM test (p-value)						
1 lag	0.008	0.000	0.000	0.000	0.000	0.000
4 lags	0.028	0.000	0.000	0.000	0.000	0.000
Hausman test1 (p-value)	0.684	0.218	0.091	0.038	0.677	0.577
Hausman test2 (p-value)	0.196	0.398	0.433	0.669	0.650	0.681

Note: Sample Jan2005-Nov2015. Standard errors based on Newey and West (1987)'s HAC covariance matrix of residuals. P-values in parentheses. The null hypothesis of the Hausman test assumes no endogeneity regarding FCI4. The Hausman test1 employs the vector of instruments $z_t^1 = [\Delta \ln(Embi_{t-h-i})]'$, whereas the test2 is based on $z_t^2 = [\Delta \ln(Selic_{t-h-i})]'$; for $i = \{0; 1; 2\}$.

[20] In Appendix E, the regression estimates based on an alternative financial conditions indicator (FCI8) are provided as a robustness check. The results are quite similar compared to those shown on Tables 8-9.

[21] In this sense, we conduct a version of the Hausman (1978) test, as suggested by Davidson and MacKinnon (1989, 1993); which is based on two OLS regressions: In the first one, we regress the suspect variable (FCI) on instruments and all exogenous variables and retrieve the residuals. Then, in the second OLS regression, we re-estimate the IS equation now including the residuals from the first regression as additional regressor. If there is no endogeneity (null hypothesis), then, the coefficient on the first stage residuals should not be significantly different from zero.

Table 9 - Regression Estimates (Industrial Production)

Regressors	h=1	h=2	h=3	h=6	h=9	h=12
	Dependent Variable: Ind.Production gap (t)					
Constant	46.899	82.398	120.261	181.158	149.116	90.744
	(0)	(0.002)	(0.005)	(0.002)	(0.009)	(0.131)
Ind.Production gap (t-h)	0.790	0.672	0.484	-0.084	-0.346	-0.465
	(0)	(0)	(0)	(0.681)	(0.049)	(0.001)
FCI4 (t-h)	-0.468	-0.823	-1.202	-1.812	-1.491	-0.906
	(0)	(0.002)	(0.005)	(0.002)	(0.009)	(0.13)
Dummy 2008	-7.823	-10.758	-11.140	-9.477	-8.304	-8.549
	(0)	(0)	(0)	(0)	(0)	(0)
R-squared	0.823	0.721	0.561	0.303	0.248	0.264
Adjusted R-squared	0.819	0.714	0.550	0.286	0.229	0.245
Residual autocorrelation LM test (p-value)						
1lag	0.000	0.001	0.000	0.000	0.000	0.000
4 lags	0.000	0.005	0.000	0.000	0.000	0.000
Hausman test1(p-value)	0.939	0.260	0.139	0.063	0.725	0.693
Hausman test2 (p-value)	0.339	0.659	0.509	0.503	0.378	0.505

Note: Sample Jan2005-Nov2015. Standard errors based on Newey and West (1987)'s HAC covariance matrix of residuals. P-values in parentheses. The null hypothesis of the Hausman test assumes no endogeneity regarding FCI4. The Hausman test1 employs the vector of instruments $z_t^1 = [\Delta \ln(Embi_{t-h-i})]'$, whereas the test2 is based on $z_t^2 = [\Delta \ln(Selic_{t-h-i})]'$; for $i = \{0; 1; 2\}$.

Notice that (in both economic proxies) the autoregressive coefficient is statistically significant (at a 5% level) for horizons up to three months, and diminishes as long as the horizon increases. At the same time, the coefficient associated to the FCI is also significant (for horizons up to nine months), and its magnitude increases, as long as the horizons increases, for horizons between one and six months. In addition, as expected, the dummy coefficient is significant in all cases, whereas the adjusted R-squared decreases for longer horizons. Finally, note the Hausman test indicates no endogeneity regarding the FCI4 in the IS-type regressions.[22]

[22] Excepting the marginal test rejection (at a 5% significance level) in the case of the IBC-BR gap for h=6 and using the first set of instruments.

3.2 Forecasting

We now move from the in-sample to the out-of-sample analysis. It is well-known in the literature that a good in-sample fit does not guarantee a good out-of-sample forecast performance (see Greene, 2003). To check for actual predictive power of the FCI in respect to economic activity movements, we conduct a (pseudo) out-of-sample empirical exercise by using 15 regressions, all based on equation (2), with forecast horizons $h = 1, ..., 12$ months.

The first point forecast (from model 1, labelled M1) is a naive random-walk forecast, in which the forecast for y_{t+h}, based on the information set available at time t, is simply the last available output gap, that is: $\widehat{y}_{t+h}^{M1} = y_t$. The second forecast (M2) is based on the AR(1) regression, such that $\widehat{y}_{t+h}^{M2} = \widehat{\alpha} + \widehat{\beta} y_t$. In turn, forecast from model M3 is given by $\widehat{y}_{t+h}^{M3} = \widehat{\alpha} + \widehat{\beta_1} y_t + \widehat{\beta_2} FCI_{t-p}$, where lag p ranges from zero to twelve months ($p = 0, ..., 12$). A dummy (control) variable is also included into models M2 and M3 to account for the 2008 global financial crisis. The proxies for the output gap are again based on the IBC-BR or industrial production series.

Forecasts are generated both by a recursive scheme (i.e., expanding sample size) as well as by a rolling window (5 years) sampling scheme. In the former, the individual models are initially estimated by using a sample that always starts at January 2005 and (initially) ends at December 2010, but it is expanded as we go into the out-of-sample period. In the latter, we keep the estimating sample size constant at 60 observations (5 years) and, then, we discard and add the oldest and newest observations, respectively, as we go into the out-of-sample period. The full forecast evaluation runs from January 2011 through November 2015 (59 observations). The results of the exercise are summarized in Tables 10-11 in terms of the mean squared forecast error (MSFE).

Table 10 - Out-of-sample forecast evaluation (MSFE)

Panel A: IBC-BR (expanding sample)

h	M1 RW	M2 AR	M3 lag0	M3 lag1	M3 lag2	M3 lag3	M3 lag4	M3 lag5	M3 lag6	M3 lag7	M3 lag8	M3 lag9	M3 lag10	M3 lag11	M3 lag12
1	1.243	1.213	1.117	1.111	1.113	1.124	1.131	1.144	1.184	1.184	1.212	1.235	1.243	1.241	1.234
2	1.911	1.843	1.543	1.552	1.583	1.612	1.653	1.755	1.819	1.863	1.931	1.986	2.013	1.983	1.988
3	2.601	2.390	1.921	1.957	1.986	2.022	2.131	2.241	2.379	2.467	2.598	2.716	2.734	2.746	2.800
4	3.071	2.735	2.362	2.424	2.426	2.409	2.450	2.564	2.717	2.873	3.068	3.183	3.275	3.360	3.420
5	3.631	3.090	2.782	2.852	2.826	2.791	2.830	2.963	3.169	3.383	3.555	3.721	3.853	3.921	3.953
6	4.200	3.442	3.454	3.525	3.494	3.343	3.282	3.377	3.583	3.761	3.973	4.168	4.285	4.341	4.456
7	4.989	3.723	3.929	4.038	3.950	3.736	3.649	3.747	3.914	4.115	4.321	4.457	4.521	4.618	4.679
8	5.847	3.833	3.939	3.995	3.897	3.753	3.780	3.930	4.158	4.373	4.525	4.595	4.667	4.697	4.749
9	6.562	3.838	3.791	3.833	3.767	3.708	3.796	4.011	4.273	4.455	4.556	4.648	4.676	4.716	4.775
10	6.525	3.871	3.752	3.781	3.765	3.790	3.941	4.174	4.383	4.498	4.613	4.658	4.698	4.757	4.886
11	7.075	3.790	3.562	3.610	3.659	3.767	3.973	4.181	4.320	4.440	4.490	4.518	4.547	4.643	4.768
12	7.407	3.714	3.453	3.514	3.580	3.706	3.890	4.041	4.200	4.277	4.326	4.363	4.449	4.558	4.646

Panel B: IBC-BR (rolling window)

h	M1 RW	M2 AR	M3 lag0	M3 lag1	M3 lag2	M3 lag3	M3 lag4	M3 lag5	M3 lag6	M3 lag7	M3 lag8	M3 lag9	M3 lag10	M3 lag11	M3 lag12
1	1.243	1.252	1.207	1.281	1.212	1.130	1.111	1.214	1.271	1.192	1.186	1.235	1.270	1.234	1.239
2	1.911	1.953	2.089	2.351	2.160	1.661	1.688	2.012	1.953	1.840	1.934	2.106	2.109	2.072	2.057
3	2.601	2.693	3.082	3.745	3.569	2.385	2.522	2.716	2.667	2.723	2.959	3.110	3.141	3.083	3.207
4	3.071	3.183	4.216	5.320	4.685	3.036	3.019	3.179	3.355	3.563	3.738	3.894	3.886	3.948	3.959
5	3.631	3.661	5.450	6.614	5.637	3.751	3.522	3.897	4.265	4.387	4.533	4.599	4.649	4.571	4.581
6	4.200	4.189	6.891	8.127	7.425	4.701	4.317	4.849	5.035	5.065	5.091	5.144	5.028	4.974	4.970
7	4.989	4.668	7.800	9.305	8.462	5.392	5.205	5.529	5.584	5.452	5.436	5.302	5.184	5.116	5.100
8	5.847	4.962	7.845	9.148	7.914	5.587	5.608	5.901	5.817	5.697	5.498	5.360	5.233	5.161	5.172
9	6.562	5.042	7.139	7.952	6.737	5.294	5.599	5.869	5.851	5.575	5.425	5.309	5.221	5.205	5.293
10	6.525	5.086	6.335	6.564	5.655	5.330	5.723	5.914	5.615	5.411	5.300	5.229	5.218	5.314	5.486
11	7.075	4.899	5.180	5.039	4.654	4.945	5.479	5.416	5.215	5.078	5.003	4.991	5.059	5.189	5.334
12	7.407	4.669	4.256	3.968	3.781	4.566	4.894	4.908	4.825	4.776	4.783	4.865	4.988	5.109	5.225

Note: Minimum MSFE for each forecast horizon (h) is marked in blue.

Firstly, notice that forecasts from model M3 (i.e. including the lagged FCI as a regressor) in several cases show better forecast performance, suggesting that a financial conditions indicator might indeed have some information content about future economic activity. Also notice that (in general) MSFEs from expanding samples are lower than respective figures from rolling window schemes.

In terms of relative MSFE, based on IBC-BR (expanding sample size, $p = 0$), the predictive gains for M3 over M1 are roughly 115% (for a one-year-horizon), and for M3 over M2 reaches 25% (for a three-month-horizon). The magnitude of MSFE gains are similar by using an economic gap based on industrial production. The statistical significance of such gains could be further checked by using (for instance) the Clark and West (2006, 2007) tests for nested models or the conditional predictive ability test of Giacomini and White (2006). We leave this route as a suggestion for future extensions of the paper.

Table 11 - Out-of-sample forecast evaluation (MSFE)

Panel A: Industrial production (expanding sample)

	M1	M2	M3	M3	M3	M3	M3	M3	M3	M3	M3	M3	M3	M3	M3
h	RW	AR	lag0	lag1	lag2	lag3	lag4	lag5	lag6	lag7	lag8	lag9	lag10	lag11	lag12
1	2.444	2.324	2.146	2.156	2.168	2.189	2.179	2.196	2.264	2.278	2.316	2.356	2.352	2.352	2.330
2	2.914	2.751	2.382	2.420	2.485	2.495	2.525	2.653	2.752	2.804	2.879	2.925	2.934	2.866	2.836
3	3.821	3.419	2.878	2.924	2.958	3.009	3.154	3.314	3.479	3.582	3.695	3.819	3.774	3.735	3.784
4	4.921	4.039	3.369	3.402	3.420	3.534	3.697	3.913	4.142	4.312	4.535	4.613	4.647	4.733	4.778
5	5.205	4.238	3.690	3.717	3.724	3.808	3.977	4.208	4.452	4.702	4.842	4.978	5.128	5.209	5.254
6	6.681	4.755	4.495	4.501	4.432	4.409	4.517	4.722	5.001	5.183	5.387	5.628	5.787	5.897	6.014
7	7.231	4.954	5.049	5.074	4.936	4.833	4.879	5.054	5.222	5.418	5.652	5.831	5.962	6.102	6.199
8	7.871	5.111	5.301	5.329	5.195	5.098	5.157	5.284	5.464	5.682	5.855	5.984	6.120	6.226	6.309
9	8.391	5.284	5.566	5.595	5.465	5.357	5.393	5.518	5.710	5.890	6.026	6.157	6.275	6.386	6.483
10	8.982	5.362	5.551	5.596	5.493	5.454	5.518	5.670	5.849	6.003	6.137	6.237	6.345	6.461	6.649
11	10.126	5.154	5.214	5.251	5.227	5.229	5.327	5.472	5.630	5.775	5.869	5.932	6.012	6.177	6.398
12	10.873	4.893	4.851	4.912	4.913	4.966	5.090	5.219	5.359	5.463	5.515	5.542	5.645	5.812	5.996

Panel B: Industrial production (rolling window)

	M1	M2	M3	M3	M3	M3	M3	M3	M3	M3	M3	M3	M3	M3	M3
h	RW	AR	lag0	lag1	lag2	lag3	lag4	lag5	lag6	lag7	lag8	lag9	lag10	lag11	lag12
1	2.444	2.396	2.356	2.387	2.153	2.189	2.188	2.365	2.424	2.341	2.360	2.417	2.461	2.448	2.346
2	2.914	2.799	3.536	3.364	2.478	2.284	2.678	3.129	3.021	2.927	3.031	3.157	3.191	3.012	2.852
3	3.821	3.653	5.116	5.341	3.603	3.094	3.825	4.169	4.127	4.163	4.387	4.541	4.403	4.214	4.313
4	4.921	4.513	6.394	6.924	4.168	3.911	4.667	5.190	5.395	5.608	5.866	5.824	5.708	5.826	5.961
5	5.205	4.964	8.034	8.034	5.012	4.601	5.457	6.128	6.393	6.545	6.500	6.445	6.593	6.702	6.762
6	6.681	5.730	9.504	9.649	6.402	5.285	6.091	6.878	7.169	7.081	7.066	7.202	7.287	7.361	7.433
7	7.231	6.107	9.713	10.061	7.154	6.230	7.013	7.465	7.271	7.118	7.179	7.208	7.223	7.279	7.291
8	7.871	6.468	9.738	10.066	7.602	7.123	7.678	7.554	7.308	7.307	7.291	7.283	7.299	7.318	7.373
9	8.391	6.758	9.294	9.210	7.699	7.683	7.767	7.609	7.545	7.463	7.424	7.407	7.400	7.464	7.609
10	8.982	6.868	8.569	8.402	7.663	7.606	7.553	7.586	7.472	7.415	7.395	7.361	7.420	7.581	7.809
11	10.126	6.547	7.086	6.827	6.614	6.666	6.942	6.969	6.931	6.915	6.883	6.910	7.013	7.190	7.471
12	10.873	6.117	5.770	5.619	5.808	6.440	6.587	6.529	6.486	6.443	6.450	6.493	6.591	6.787	7.024

Note: Minimum MSFE for each forecast horizon (h) is marked in blue.

3.3 Risk Analysis

In this section, we go beyond the usual conditional-mean analysis (presented in the previous section) and extend our empirical investigation, regarding FCI and economic activity, to a conditional density framework. This extended approach enables us to conduct risk-analysis exercises and construct conditional probabilities in respect to a set of pre-established scenarios.

It is important to highlight that the objective here is not to propose a competing forecasting model for economic activity, but rather to increase our understanding of its dynamics from a risk-analysis point of view. In other words, we investigate potential asymmetric linkages between lagged FCI and economic activity proxies that a simple point forecast evaluation may neglect.

To do so, we generate a set of conditional density forecasts, for a full range of forecast horizons. The density forecasts are generated by using a semiparametric approach based on quantile regression, as suggested by Gaglianone and Lima (2012).[23] By using standard quantile regression techniques (see Koenker, 2005), the conditional quantiles of y_{t+h} (which denotes the economic activity gap, based on IBC-BR or industrial production), using the information set $\mathcal{F}_t$ available at time t, can be modeled by the following linear representation:

$$Q_\tau(y_{t+h} \mid \mathcal{F}_t) = \mathbf{X}_t'\boldsymbol{\theta}_h(\tau) \tag{3}$$

where $\mathbf{X}_t'$ is a covariate vector, $\tau \in [0;1]$ is a quantile level of interest, and $\boldsymbol{\theta}_h(\tau)$ is a vector of model parameters. To simplify notation, we also denote $Q_\tau(y_{t+h} \mid \mathcal{F}_t)$ by $Q_\tau(y_{t+h|t})$. Following the conditional mean dynamics presented in equation (2), we adopt the same set of covariates $\mathbf{X}_t' = [c; y_t; FCI_t; z_t]$; where c denotes the intercept, and a dummy variable for the 2008 shock is considered in z_t. The sample covers the period from January 2005 to November 2015 ($T = 131$ observations).

Further details on the risk-analysis' setup are presented in Appendix A, which is used to generate the fan charts of future economic activity; based on forecast horizons $h = 1, ..., 13$ months (in order to produce density forecasts up to December 2016) and on a discrete set of quantile levels $\tau = [0.01; 0.02; ...; 0.99]$. Regarding multi-period forecast horizons ($h > 1$), we follow the same "direct-forecast approach" discussed in the previous section. Finally, given a family of estimated conditional quantiles $\widehat{Q}_\tau(\cdot)$, the respective conditional probability density function (pdf) can easily be estimated by using the Epanechnikov kernel, for instance, which is a weighting function that determines the shape of the bumps.

Table 12 - Descriptive statistics of the PDFs

IBC-BR	Mar-16	Jun-16	Sep-16	Dec-16
Mean	135.79	135.61	136.06	136.41
Median	136.09	136.02	135.74	135.97
Std. Dev.	4.70	6.40	7.31	8.67
Skewness	-0.39	-0.18	0.13	0.10

Ind. Production	Mar-16	Jun-16	Sep-16	Dec-16
Mean	83.07	82.67	83.87	83.54
Median	84.01	83.82	83.67	83.41
Std. Dev.	6.89	9.29	9.63	12.00
Skewness	-0.85	-0.50	0.16	0.00

[23] The authors generate multi-step-ahead conditional density forecasts for the unemployment rate in the U.S. from (point) consensus forecasts and quantile regression; which is a setup that do not impose any parametric structure on the shape of the conditional distributions.

Figure 8 - Probability Density Functions (PDFs) for the IBC-BR (left) and Industrial Production (right)

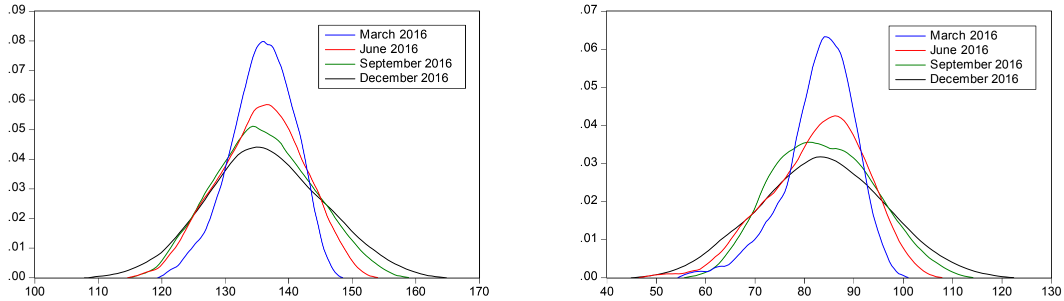
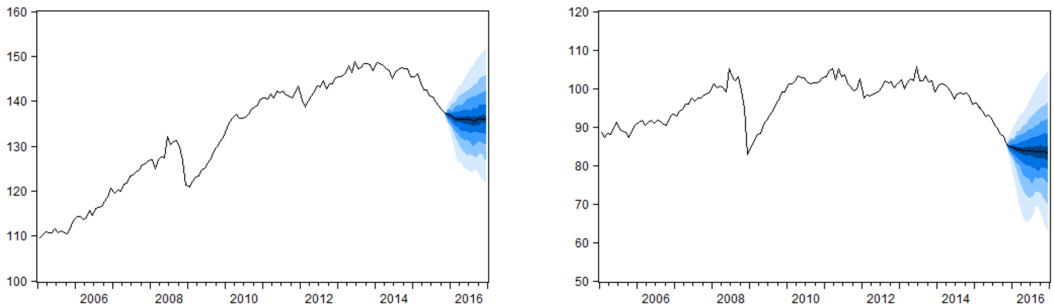


Figure 9 - Fan chart for the seasonally adjusted level of the IBC-BR (left) and Industrial Production (right)



Notes: Estimation sample Jan2005-Nov2015. The darkest blue area contains the conditional quantiles from τ =0.45 to 0.55, whereas the fan-chart "edges" represents τ =0.05 and 0.95. The black line in the out-of-sample period (after November 2015) indicates the median forecasts for h=1,...,13 months. Graphs are based, for illustrative purposes, on the average trend variation along the last 12 months (IBC-BR) or 36 months (industrial production).

Notice the negative skewness in both densities along the first semester of 2016, probably due to the negative (and severe) shock on economic activity after the 2008 crisis. Also note that forecast uncertainty (e.g. standard deviation), as expected, increases as long as the forecast horizon augments. Based on the conditional quantiles (estimated for a grid of quantile levels) and related conditional densities (PDFs), it is straightforward to compute conditional probabilities given (*ad hoc*) scenarios.[24]

[24] To do so, for each out-of-sample period $T + h$, a simple search along the grid of estimated conditional quantiles will reveal which is the quantile level τ^* that minimizes the distance between such conditional quantiles and the respective output growth rate assumed in the referred scenario. Thus, the probability that future output growth will surpass the scenario's growth is given by $(1 - \tau^*)$.

The results are presented in Table 13, in which the output growth rates computed from our density model are compared to year-over-year (yoy) growth rates of 0% or -3%. Of course, the results will heavily depend on the assumed output trend (see Appendix A), since the forecast for the location of the distribution is key for all estimated conditional densities (and the respective calculation of probabilities). To simplify and overcome the uncertainty regarding future output trend, we investigate the results for different cases (i.e. different output growth rates). For comparison purposes, we also present the growth rates expected by market agents surveyed by the Banco Central do Brasil.

Table 13 - Point forecasts and conditional probabilities

IBC-BR

	Growth rates (%) for 2016		Probability (%) of growth rate (yoy)	
	year-over-year	*Q4-over-Q4*	*< -3%*	*< 0%*
Median (Focus) survey expectation *(as of January 15th, 2016)*	-2.99	-1.20	-	-
Point forecasts from QR model *(last year's monthly trend growth)*	-3.70	-1.07	36	58
Point forecasts from QR model *(50% of last year's monthly trend growth)*	-2.51	0.78	22	42

Industrial Production

	Growth rates (%) for 2016		Probability (%) of growth rate (yoy)	
	year-over-year	*Dec.-over-Dec.*	*< -3%*	*< 0%*
Median (Focus) survey expectation *(as of January 15th, 2016)*	-3.47	-1.00	-	-
Point forecasts from QR model *(last 3 years' monthly trend growth)*	-7.96	-1.71	48	57
Point forecasts from QR model *(50% of last 3 years' monthly trend growth)*	-6.36	0.81	39	50

Notes: Survey expectations are from the Focus dataset (in January 15th, 2016). Regarding the first table, since expectations for IBC-BR are not available, we present (just for comparison purposes) median survey-based expectations for the real GDP growth rate.

It is worth mentioning that the density forecast setup used here for risk analysis is merely constructed to illustrate the potential usefulness of the FCI in explaining future economic dynamics. We are not claiming that this reduced-form (and parsimonious) approach is a competing one to predict output (in terms of MSFE, log-score or other measure) but, instead, we try to shed some light on the potential range of tools and applications that the proposed modified IS-type of equation (by replacing the real interest rates by a broader measure of financial conditions) might provide.

4 Conclusion

Since the aftermath of the global crisis of 2008, it is paramount for policymakers and market participants to properly monitor the financial conditions of the economy together with the usual economic activity prospects. A recent tool developed to help understanding the dynamics of the financial markets (and its implications on the business cycles) is the Financial Conditions Indicator - FCI. Although there is no consensus in the literature on the best way to construct an FCI, the main idea is to employ a vast set of variables, with valuable information from different aspects of the economy (e.g. different markets), which is used to generate a single time series that summarizes this richer information set (when compared, for instance, to the single nominal policy interest rate).

In this paper, we propose a competing methodology to construct distinct FCIs, which can be used to monitor the financial conditions of the economy and be further employed to forecast economic activity. An empirical exercise is provided to illustrate the methodology, in which a modified IS equation (substituting the interest rate by the FCI) is employed to point forecast the output gap in Brazil. Moreover, we use a quantile regression technique to construct density forecasts and generate the fan charts of future economic activity. A risk analysis is also conducted within this setup in order to compute conditional probabilities of the output growth to be above (or below) a given scenario.

Suggestions for future extensions might include: (i) using real-time data; (ii) exploring the one-sided HP-filter to estimate in-sample trend (instead of the standard two-sided version of the HP filter); or (iii) including other covariates in the modified IS equation; among others.

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Appendix A - Risk Analysis Setup

Assume that the level of economic activity ($\widetilde{y}_{t+h}$) can be decomposed into "cycle-trend" components, such that $\widetilde{y}_{t+h}$ is given by the sum of the output gap (y_{t+h}) with the potential output[25] (or trend) y^*_{t+h}, such that:

$$\widetilde{y}_{t+h} = y_{t+h} + y^*_{t+h} \tag{4}$$

The h-period difference of the previous decomposition leads to $\Delta^h \widetilde{y}_{t+h} \equiv \widetilde{y}_{t+h} - \widetilde{y}_t = \Delta^h y_{t+h} + \Delta^h y^*_{t+h}$. Assume (for simplicity) that $\Delta^h y_{t+h}$ and $\Delta^h y^*_{t+h}$ are covariance-stationary and comonotonic random variables.[26] Thus, it follows that quantile functions of their sums are equal to the sum of quantiles (see Koenker, 2005):

$$Q_\tau(\Delta^h \widetilde{y}_{t+h|t}) = Q_\tau(\Delta^h y_{t+h|t}) + Q_\tau(\Delta^h y^*_{t+h|t}) \tag{5}$$

Note that $Q_\tau(\Delta^h y_{t+h|t}) = Q_\tau(y_{t+h} - y_t \mid \mathcal{F}_t) = Q_\tau(y_{t+h|t}) - y_t = \mathbf{X}'_t \boldsymbol{\theta}_h(\tau) - y_t$. The finite sample counterpart[27] of $Q_\tau(\Delta^h y_{t+h|t})$ is given by

$$\widehat{Q}_\tau(\Delta^h y_{t+h|t}) = \mathbf{X}'_t \widehat{\boldsymbol{\theta}}_h(\tau) - y_t \tag{6}$$

In respect to the last term on equation (5), assume that (out-of-sample) trend variation $\Delta^h y^*_{t+h|t} \equiv y^*_{t+h|t} - y^*_t$ (i.e. forecast of $\Delta^h y^*_{t+h}$ conditional on $\mathcal{F}_t$) follows a normal distribution, such that $\Delta^h y^*_{t+h|t} \sim N(\mu_h; \sigma^2_h)$, in which the mean μ_h is proxied here by the sample average of past trend (one-period) variations multiplied by the amount h of forecast horizons, so that: $\widehat{\mu}_h = \frac{h}{(t_2 - t_1 + 1)} \sum_{t=t_1}^{t_2} \Delta y^*_t$; $t_1 < t_2 \leqslant T$. The variance σ^2_h is proxied by the sample variance of (one-period) trend variations, multiplied by the square of h times a δ parameter[28], such that: $\widehat{\sigma}^2_h = \frac{(h\delta)^2}{(t_2 - t_1 + 1)} \sum_{t=t_1}^{t_2} (\Delta y^*_t - \widehat{\mu}_h)^2$. Thus, it follows that:

$$\widehat{Q}_\tau(\Delta^h y^*_{t+h|t}) = \widehat{\mu}_h + \widehat{\sigma}_h \Phi^{-1}(\tau) \tag{7}$$

where Φ^{-1} denotes the inverse of the cumulative distribution function (cdf) of a standard normal distribution. This way, by combining the previous equations, it follows that:

$$\widehat{Q}_\tau(\Delta^h \widetilde{y}_{T+h|T}) = \Big(\mathbf{X}'_T \widehat{\boldsymbol{\theta}}_h(\tau) - y_T\Big) + \widehat{\mu}_h + \widehat{\sigma}_h \Phi^{-1}(\tau) \tag{8}$$

Therefore, the conditional forecast of $\Delta^h \widetilde{y}_{T+h}$ depends on the sum of the following terms: (i) the estimated conditional quantile of the economic gap ($\mathbf{X}'_T \widehat{\boldsymbol{\theta}}_h(\tau)$) minus

[25] In-sample economic trend y^*_t (i.e. $t \leqslant T$) is estimated by using a standard HP filter.

[26] Two random variables $X, Y : \Omega \to \mathbb{R}$ are said to be comonotonic if there exists a third random variable $Z : \Omega \to \mathbb{R}$ and increasing functions f and g such that $X = f(Z)$ and $Y = g(Z)$.

[27] Consistency of such estimator relies on the asymptotics and related consistency of standard linear conditional quantile estimators (see Koenker, 2005).

[28] The calibrated δ parameter controls the magnitude of uncertainty regarding the future economic trend *vis-à-vis* the uncertainty related to the density forecasts of the economic gap.

the economic gap observed in last sample period y_T; (ii) the estimate of average trend (h-period) variation $\widehat{\mu}_h$; and (iii) an additional term $\widehat{\sigma}_h\Phi^{-1}(\tau)$ to account for uncertainty in respect to the path of the future trend. One can add to both sides of previous equation the last observed level $\widetilde{y}_T$ of the economic activity, such that:

$$\begin{aligned}
\widehat{Q}_\tau(\Delta^h\widetilde{y}_{T+h|T}) + \widetilde{y}_T &= \left(\mathbf{X}_T'\widehat{\boldsymbol{\theta}}_h(\tau) - y_T\right) + \widehat{\mu}_h + \widehat{\sigma}_h\Phi^{-1}(\tau) + \widetilde{y}_T && (9)\\
&= y_T^* + \widehat{\mu}_h + \mathbf{X}_T'\widehat{\boldsymbol{\theta}}_h(\tau) + \widehat{\sigma}_h\Phi^{-1}(\tau) && (10)\\
&= \widehat{y}_{T+h|T}^* + \mathbf{X}_T'\widehat{\boldsymbol{\theta}}_h(\tau) + \widehat{\sigma}_h\Phi^{-1}(\tau) && (11)
\end{aligned}$$

where $\widetilde{y}_T = y_T + y_T^*$ and $\widehat{y}_{T+h|T}^* \equiv y_T^* + \widehat{\mu}_h$ is the (point) forecast for y_{T+h}^* conditional on $\mathcal{F}_T$. Now define a Value-at-Risk (VaR) measure of the economic activity. If $\widetilde{y}_{T+h}$ denotes the output level at future period $T+h$, and $\tau \in [0;1]$ denotes a (pre-determined) significance level, then the respective VaR (denoted by $V_{T+h,\tau}$) can implicitly be defined by the following expression

$$\Pr\left[\widetilde{y}_{T+h} > V_{T+h,\tau}|\mathcal{F}_T\right] = (1-\tau) \qquad (12)$$

where $\mathcal{F}_T$ is the information set available at T. Notice from previous definition that

$$\begin{aligned}
\Pr\left[\widetilde{y}_{T+h} - \widetilde{y}_T > V_{T+h,\tau} - \widetilde{y}_T|\mathcal{F}_T\right] &= (1-\tau) && (13)\\
\Pr\left[\Delta^h\widetilde{y}_{T+h} < V_{T+h,\tau} - \widetilde{y}_T|\mathcal{F}_T\right] &= \tau && (14)
\end{aligned}$$

Notice that last equation embodies the definition of a conditional quantile of $\Delta^h\widetilde{y}_{T+h}$, such that:

$$\begin{aligned}
Q_\tau(\Delta^h\widetilde{y}_{T+h|T}) &= V_{T+h,\tau} - \widetilde{y}_T && (15)\\
V_{T+h,\tau} &= Q_\tau(\Delta^h\widetilde{y}_{T+h|T}) + \widetilde{y}_T && (16)
\end{aligned}$$

By using equation (11), an estimate for $V_{T+h,\tau}$ is, thus, given by

$$\begin{aligned}
\widehat{V}_{T+h,\tau} &= \widehat{Q}_\tau(\Delta^h\widetilde{y}_{T+h|T}) + \widetilde{y}_T && (17)\\
&= \widehat{y}_{T+h|T}^* + \mathbf{X}_T'\widehat{\boldsymbol{\theta}}_h(\tau) + \widehat{\sigma}_h\Phi^{-1}(\tau) && (18)\\
&= (y_T^* + \widehat{\mu}_h) + \mathbf{X}_T'\widehat{\boldsymbol{\theta}}_h(\tau) + \widehat{\sigma}_h\Phi^{-1}(\tau) && (19)
\end{aligned}$$

Finally, based on a set of estimates $\widehat{V}_{T+h,\tau}$, for $h = 1, ..., H$ and for $\tau = [\tau_1; \tau_2; ...; \tau_N]$ one can construct the "fan chart" for future economic activity, which simply represents an out-of-sample (point) forecast embodied with an uncertainty measure.

Appendix B - Raw Data

Figure B1 - CPI inflation (IPCA) and nominal interest rates (% p.a.)

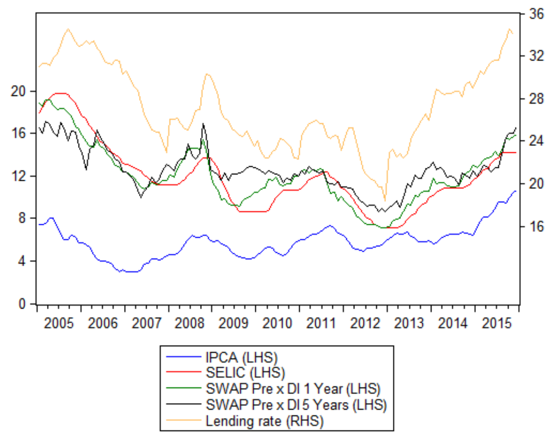


Figure B2 - CDS spread, Embi+BR and VIX

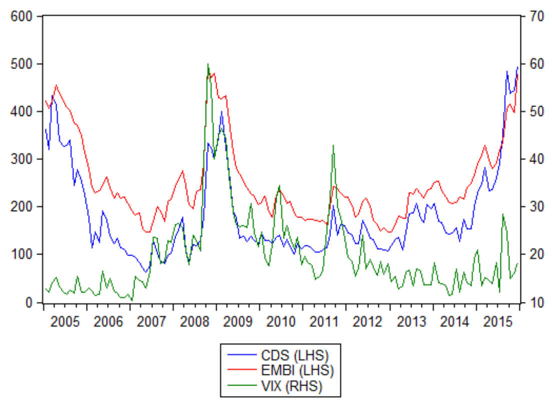


Figure B3 - Nominal monetary aggregates (R$ thousand)

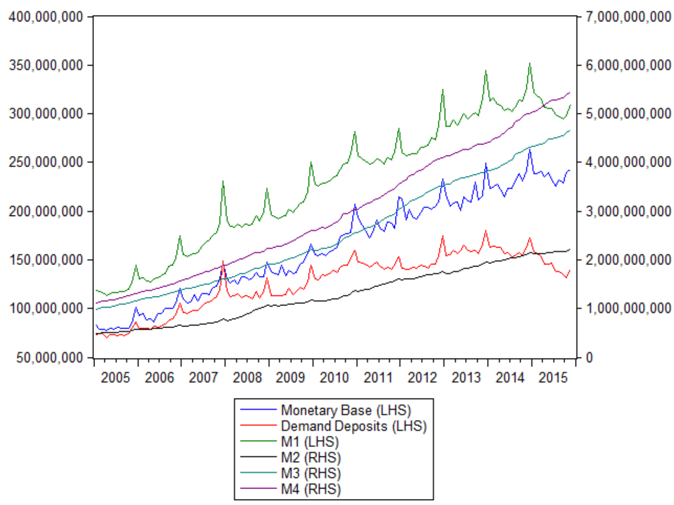


Figure B4 - Nominal credit operations outstanding
(R$ million, nonearmarked operations)

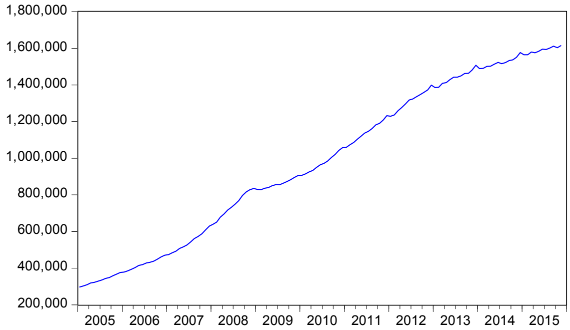


Figure B5 - Credit-to-GDP ratio
(total credit operations in the financial system)

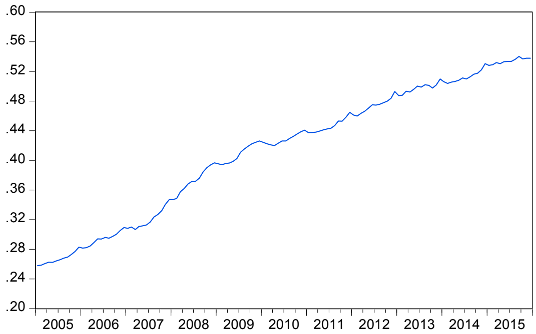


Figure B6 - Banking credit indicators

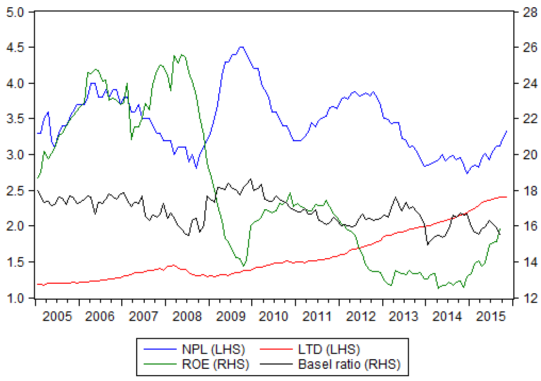


Figure B7 - Capital Markets

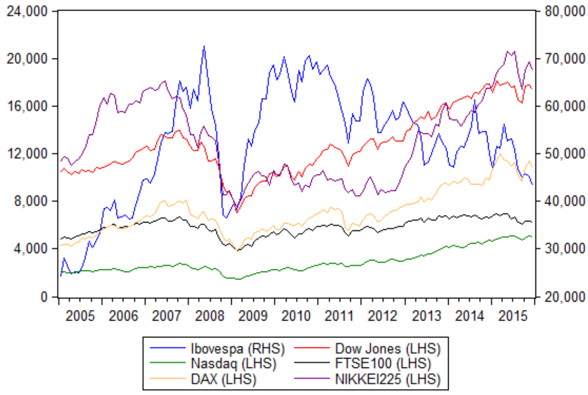


Figure B8 - Ten-year U.S. Treasury (% p.a.) and Real effective exchange rate (index)

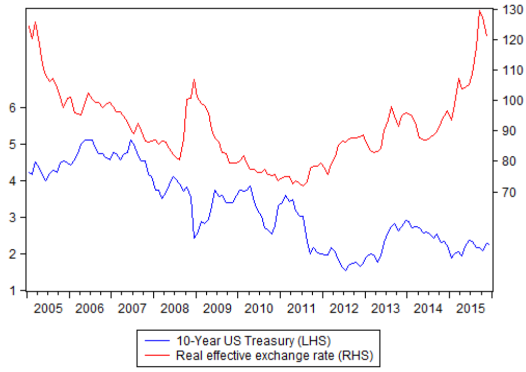
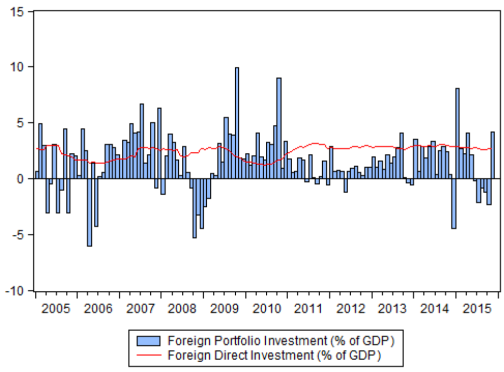


Figure B9 - Capital Flows (FDI and FPI)



Appendix C - Principal Component Analysis (PCA)

Table C1 - PCA for Group1 (left) and Group2 (right)

Principal Components Analysis
Date: 04/04/16 Time: 14:33
Sample: 2005M01 2015M12
Included observations: 132
Computed using: Ordinary correlations
Extracting 5 of 5 possible components

Eigenvalues: (Sum = 5, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.245954	2.226748	0.6492	3.245954	0.6492
2	1.019206	0.573091	0.2038	4.26516	0.853
3	0.446115	0.222003	0.0892	4.711275	0.9423
4	0.224112	0.1595	0.0448	4.935388	0.9871
5	0.064612	---	0.0129	5	1

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5
Selic (policy interest rate)	0.50348	-0.31002	0.293579	0.164483	-0.73291
Swap Pre x DI 1 year	0.498012	-0.32633	0.224434	0.399777	0.659773
Slope of the term structure	-0.44457	0.046719	0.893293	0.026671	0.038646
Lending rate	0.486557	0.252408	0.245913	-0.785274	0.149747
CDS spread	0.253207	0.855281	0.070679	0.442445	-0.06023

Principal Components Analysis
Date: 04/04/16 Time: 14:37
Sample: 2005M01 2015M12
Included observations: 132
Computed using: Ordinary correlations
Extracting 5 of 5 possible components

Eigenvalues: (Sum = 5, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.04216	1.670743	0.6084	3.04216	0.6084
2	1.371417	0.955812	0.2743	4.413578	0.8827
3	0.415605	0.284761	0.0831	4.829183	0.9658
4	0.130844	0.090871	0.0262	4.960027	0.992
5	0.039973	---	0.008	5	1

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5
Real growth of credit outstanding	0.505785	0.375541	-0.04101	-0.199155	0.749537
NPL	-0.30007	0.614548	0.700259	-0.171044	-0.11256
LTD	-0.55376	0.033647	-0.02496	0.643735	0.526496
ROE	0.470712	0.434655	-0.07302	0.674058	-0.36031
Basel ratio	0.354846	-0.53967	0.708521	0.249666	0.136042

Table C2 - PCA for Group3 (left) and Group4 (right)

Principal Components Analysis
Date: 04/04/16 Time: 14:41
Sample: 2005M01 2015M12
Included observations: 132
Computed using: Ordinary correlations
Extracting 6 of 6 possible components

Eigenvalues: (Sum = 6, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	4.052862	2.834044	0.6755	4.052862	0.6755
2	1.218819	0.784258	0.2031	5.271681	0.8786
3	0.434561	0.200681	0.0724	5.706242	0.951
4	0.23388	0.180842	0.039	5.940121	0.99
5	0.053038	0.046196	0.0088	5.993159	0.9989
6	0.006841	---	0.0011	6	1

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Monetary base	0.435472	-0.21106	-0.0185	0.868495	0.104055	0.019091
Demand deposits	0.430031	-0.38924	0.280009	-0.340298	0.179579	0.661142
M1	0.442955	-0.35098	0.27616	-0.271215	-0.12107	-0.71842
M2	0.224002	0.701352	0.67111	0.075434	-0.03066	0.03014
M3	0.417537	0.369911	-0.46779	-0.203251	0.640812	-0.13435
M4	0.452453	0.228104	-0.41925	-0.096724	-0.72848	0.165651

Principal Components Analysis
Date: 04/04/16 Time: 14:44
Sample: 2005M01 2015M12
Included observations: 132
Computed using: Ordinary correlations
Extracting 6 of 6 possible components

Eigenvalues: (Sum = 6, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	4.25921	3.075035	0.7099	4.25921	0.7099
2	1.184175	0.806795	0.1974	5.443385	0.9072
3	0.37738	0.232774	0.0629	5.820766	0.9701
4	0.144606	0.123034	0.0241	5.965371	0.9942
5	0.021572	0.008516	0.0036	5.986944	0.9978
6	0.013056	---	0.0022	6	1

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Ibovespa	0.079464	0.881629	0.33311	0.263451	0.187397	-0.03049
Dow Jones	0.47502	0.01919	-0.24059	-0.220715	0.324256	-0.74983
Nasdaq	0.455695	0.033396	-0.51825	0.188692	0.398777	0.572729
FTSE100	0.448387	0.047196	0.416947	-0.714864	-0.09623	0.32029
DAX	0.471839	0.111295	-0.17785	0.276163	-0.80744	-0.07163
Nikkei225	0.36973	-0.45457	0.597577	0.508898	0.198758	-0.03299

Table C3 - PCA for Group5

Principal Components Analysis
Date: 04/04/16 Time: 14:47
Sample: 2005M01 2015M12
Included observations: 132
Computed using: Ordinary correlations
Extracting 6 of 6 possible components

Eigenvalues: (Sum = 6, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	2.167411	0.552565	0.3612	2.167411	0.3612
2	1.614846	0.447454	0.2691	3.782257	0.6304
3	1.167392	0.587165	0.1946	4.949649	0.8249
4	0.580227	0.210915	0.0967	5.529877	0.9216
5	0.369312	0.268501	0.0616	5.899189	0.9832
6	0.100811	---	0.0168	6	1

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
REER	0.616834	0.130065	-0.14697	-0.337552	0.189132	0.656724
FDI	-0.12895	0.652142	0.267996	0.255445	0.648842	-0.00364
FPI	0.502186	-0.03311	-0.19456	0.832733	-0.11467	-0.04762
Embi+BR	0.583599	-0.08461	0.360164	-0.285803	0.161172	-0.64411
10-Year US Treasury	0.100544	0.691982	0.135951	-0.099763	-0.69269	-0.05285
VIX	-0.00111	-0.26589	0.848837	0.189015	-0.15583	0.385701

Table C4 - PCA for All Variables

Principal Components Analysis
Date: 04/04/16 Time: 14:58
Sample: 2005M01 2015M12
Included observations: 132
Computed using: Ordinary correlations
Extracting 28 of 28 possible components

Eigenvalues: (Sum = 28, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	10.88426	4.94144	0.3887	10.88426	0.3887
2	5.942817	1.443000	0.2122	16.82707	0.6010
3	4.499817	2.530936	0.1607	21.32689	0.7617
4	1.968881	0.786074	0.0703	23.29577	0.832
5	1.182807	0.272285	0.0422	24.47858	0.8742
6	0.910522	0.204344	0.0325	25.3891	0.9068
7	0.706178	0.260936	0.0252	26.09528	0.932
8	0.445242	0.114448	0.0159	26.54052	0.9479
9	0.330794	0.092159	0.0118	26.87132	0.9597
10	0.238635	0.036667	0.0085	27.10995	0.9682
11	0.201968	0.026651	0.0072	27.31192	0.9754
12	0.175316	0.060643	0.0063	27.48723	0.9817
13	0.114673	0.038944	0.0041	27.60191	0.9858
14	0.075729	0.007929	0.0027	27.67764	0.9885
15	0.067800	0.018669	0.0024	27.74544	0.9909
16	0.049132	0.002745	0.0018	27.79457	0.9927
17	0.046386	0.011848	0.0017	27.84095	0.9943
18	0.034538	0.002506	0.0012	27.87549	0.9956
19	0.032032	0.008628	0.0011	27.90752	0.9967
20	0.023403	0.00349	0.0008	27.93093	0.9975
21	0.019914	0.005959	0.0007	27.95084	0.9982
22	0.013955	0.003837	0.0005	27.9648	0.9987
23	0.010117	0.001065	0.0004	27.97491	0.9991
24	0.009052	0.002379	0.0003	27.98397	0.9994
25	0.006674	0.002677	0.0002	27.99064	0.9997
26	0.003996	0.000755	0.0001	27.99464	0.9998
27	0.003241	0.001118	0.0001	27.99788	0.9999
28	0.002123	---	0.0001	28.00000	1

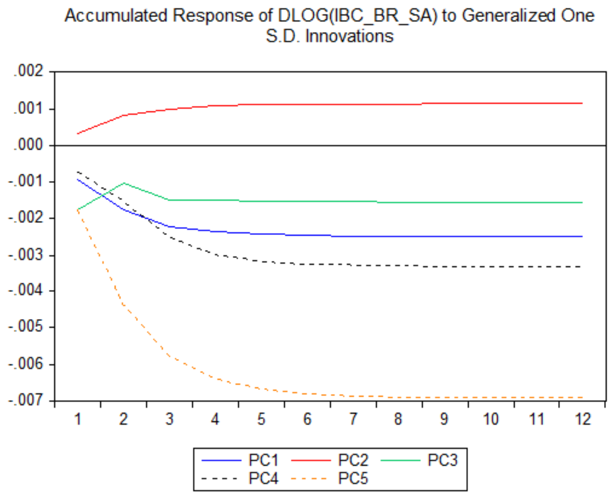
Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8
Selic (policy interest rate)	0.205138	0.261754	-0.11573	-0.008932	-0.07419	0.042073	0.179432	0.131217
Swap Pre x DI 1 year	0.194144	0.249643	-0.16896	-0.029692	0.141098	0.059749	0.104905	0.173088
Slope of the term structure	-0.04276	-0.26012	0.187583	0.13594	-0.11138	0.201655	-0.59937	0.207499
Lending rate	0.017103	0.37247	-0.08316	0.006388	-0.08231	0.282607	0.075609	0.154027
CDS spread	-0.07226	0.316495	0.208287	-0.003515	0.228086	-0.04521	-0.07888	-0.32586
Real growth of credit outstanding	-0.26305	-0.04093	-0.00484	0.274093	0.153238	0.076319	0.172876	0.047381
NPL	0.14803	-0.14985	0.083533	0.465178	-0.1652	0.274928	-0.02681	-0.21749
LTD	0.297316	-0.00141	0.043429	0.03143	-0.02837	-0.0699	0.077213	0.120274
ROE	-0.23934	-0.09698	0.07327	0.287355	0.144017	-0.20089	0.158892	0.048144
Basel ratio	-0.1839	0.003462	0.045661	-0.425125	-0.31653	0.099464	0.076609	-0.00859
Monetary base	-0.21066	0.059497	0.24454	0.065671	-0.06501	0.132905	-0.05904	0.242238
Demand deposits	-0.2049	0.104348	0.245591	-0.058731	-0.17206	0.321679	0.258389	-0.017
M1	-0.21184	0.103455	0.242411	-0.021665	-0.15796	0.27374	0.293089	0.045227
M2	-0.19944	-0.01148	-0.22652	0.305357	0.167133	0.037143	0.086215	-0.32874
M3	-0.24704	0.12432	0.000132	0.020493	0.346361	-0.0302	-0.15369	0.345597
M4	-0.2459	0.1371	0.092671	0.117621	0.204829	-0.13531	-0.03928	0.398512
Ibovespa	0.058927	0.359457	0.059357	0.105644	-0.1573	-0.16089	-0.06523	0.056262
Dow Jones	0.258412	-0.02744	0.221224	0.06688	0.117443	0.035771	0.089959	0.063053
Nasdaq	0.283455	-0.04473	0.143584	0.025786	0.020234	-0.05811	0.016708	0.059155
FTSE100	0.178578	0.029131	0.35902	0.031119	0.169278	0.026753	0.085924	-0.07851
DAX	0.259206	0.001323	0.208535	0.094291	0.027481	-0.11024	0.146095	0.086965
Nikkei225	0.100784	-0.19595	0.329209	0.013501	0.125945	-0.23356	0.289009	0.060894
REER	-0.02458	0.368197	-0.00206	0.126442	-0.0427	-0.09653	-0.25385	-0.34966
FDI	0.171466	-0.01267	-0.14445	0.185563	0.274273	0.571291	0.078251	0.031737
FPI	0.03025	0.180698	0.224032	0.360284	-0.44817	-0.12979	-0.12392	0.07927
Embi+BR	0.006287	0.328834	0.228117	-0.072782	0.221005	-0.02228	-0.11351	-0.15761
10-Year US Treasury	0.234137	0.132787	-0.19481	0.035348	0.031588	0.090822	-0.18586	0.250883
VIX	0.064501	-0.06463	0.320261	-0.309604	0.265095	0.24418	-0.26639	-0.1439

Note: We only show the results from PC1 until PC8 since they jointly account for roughly 95% of cumulative proportion.

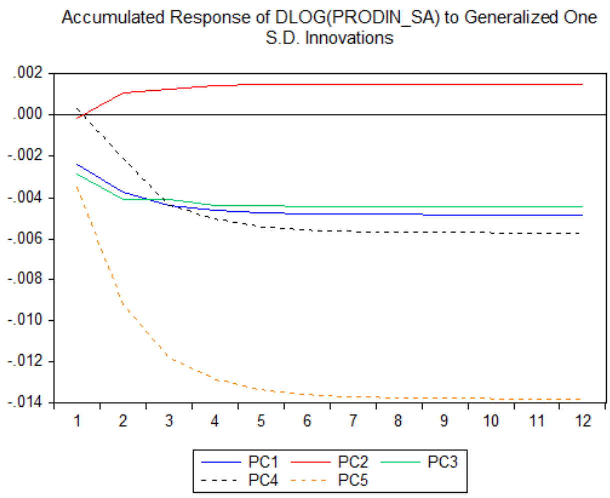
Appendix D - Impulse-response functions

Figure D1 - Impulse-response functions (IBC-BR)



Note: The graphs above are based on the "generalized impulse" methodology of Pesaran and Shin (1998) to construct the impulse-response functions, based on an orthogonal set of innovations that does not depend on the VAR ordering.

Figure D2 - Impulse-response functions (Industrial Production)



Note: The graphs above are based on the "generalized impulse" methodology of Pesaran and Shin (1998) to construct the impulse-response functions, based on an orthogonal set of innovations that does not depend on the VAR ordering.

Appendix E - Alternative IS-type regressions

Table E1 - Regression Estimates (IBC-BR)

Dependent Variable: IBC-BR gap (t)

Regressors	h=1	h=2	h=3	h=6	h=9	h=12
Constant	30.962	61.786	91.983	125.498	108.557	58.022
	(0.005)	(0.006)	(0.008)	(0.004)	(0.007)	(0.074)
IBC-BR gap (t-h)	0.822	0.681	0.487	-0.034	-0.349	-0.429
	(0)	(0)	(0)	(0.871)	(0.068)	(0.001)
FCI8 (t-h)	-0.309	-0.618	-0.920	-1.255	-1.085	-0.579
	(0.005)	(0.006)	(0.009)	(0.004)	(0.007)	(0.072)
Dummy 2008	-4.076	-5.815	-6.069	-4.822	-4.426	-3.736
	(0)	(0)	(0)	(0)	(0)	(0)
R-squared	0.821	0.703	0.557	0.278	0.206	0.176
Adjusted R-squared	0.817	0.696	0.546	0.260	0.186	0.154
Residual autocorrelation LM test (p-value)						
1lag	0.015	0.000	0.000	0.000	0.000	0.000
4 lags	0.067	0.000	0.000	0.000	0.000	0.000
Hausman test1 (p-value)	0.476	0.177	0.065	0.027	0.590	0.512
Hausman test2 (p-value)	0.665	0.976	0.825	0.205	0.294	0.425

Note: Sample Jan2005-Nov2015. Standard errors based on Newey and West (1987)'s HAC covariance matrix of residuals. P-values in parentheses. The null hypothesis of the Hausman test assumes no endogeneity regarding FCI8. The Hausman test1 employs the vector of instruments $z_t^1 = [\Delta \ln(Embi_{t-h-i})]'$, whereas the test2 is based on $z_t^2 = [\Delta \ln(Selic_{t-h-i})]'$; for $i = \{0; 1; 2\}$.

Table E2 - Regression Estimates (Industrial Production)

Dependent Variable: Ind.Production gap (t)

Regressors	h=1	h=2	h=3	h=6	h=9	h=12
Constant	41.921	72.912	106.267	153.319	119.026	68.074
	(0.013)	(0.03)	(0.045)	(0.016)	(0.029)	(0.122)
Ind.Production gap (t-h)	0.790	0.672	0.483	-0.083	-0.336	-0.453
	(0)	(0)	(0)	(0.706)	(0.071)	(0.002)
FCI8 (t-h)	-0.419	-0.728	-1.062	-1.533	-1.190	-0.679
	(0.013)	(0.031)	(0.046)	(0.017)	(0.029)	(0.12)
Dummy 2008	-7.772	-10.700	-11.123	-9.038	-7.778	-7.996
	(0)	(0)	(0)	(0)	(0)	(0)
R-squared	0.820	0.711	0.542	0.254	0.208	0.247
Adjusted R-squared	0.816	0.704	0.531	0.236	0.187	0.227
Residual autocorrelation LM test (p-value)						
1lag	0.000	0.000	0.000	0.000	0.000	0.000
4 lags	0.000	0.002	0.000	0.000	0.000	0.000
Hausman test1 (p-value)	0.764	0.325	0.141	0.048	0.765	0.539
Hausman test2 (p-value)	0.884	0.152	0.115	0.153	0.151	0.286

Note: Sample Jan2005-Nov2015. Standard errors based on Newey and West (1987)'s HAC covariance matrix of residuals. P-values in parentheses. The null hypothesis of the Hausman test assumes no endogeneity regarding FCI8. The Hausman test1 employs the vector of instruments $z_t^1 = [\Delta \ln(Embi_{t-h-i})]'$, whereas the test2 is based on $z_t^2 = [\Delta \ln(Selic_{t-h-i})]'$; for $i = \{0; 1; 2\}$.