IDB WORKING PAPER SERIES Nº IDB-WP-826

Financial Conditions Indicator for Brazil

Wagner Piazza Gaglianone
Waldyr Dutra Areosa

Inter-American Development Bank
Department of Research and Chief Economist

August 2017

Financial Conditions Indicator for Brazil

Wagner Piazza Gaglianone*
Waldyr Dutra Areosa**

* Central Bank of Brazil
** Central Bank of Brazil and PUC-Rio

August 2017

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Gaglianone, Wagner Piazza.
Financial conditions indicator for Brazil / Wagner Piazza Gaglianone, Waldyr Dutra Areosa; editor, John Dunn Smith.
p. cm. — (IDB Working Paper Series ; 826)
Includes bibliographic references.
1. Brazil-Economic conditions-Econometric models. 2. Economic forecasting-Brazil. I. Dutra Areosa, Waldyr. II. Smith, J. D., 1963-, editor. III. Inter-American Development Bank. Department of Research and Chief Economist. IV. Title. V. Series.
IDB-WP-826

http://www.iadb.org

Abstract[*]

This paper proposes a methodology for constructing a Financial Conditions Indicator (FCI) based on factor analysis and the approaches of Brave and Butters (2011) and Aramonte et al. (2013). A selected set of variables is used and their information content aggregated into a single index that summarizes the overall financial conditions of the economy. The approach is further employed to forecast economic activity. An empirical exercise for Brazil is provided to illustrate the methodology, in which a reduced-form equation is employed to point forecast the growth rate of the Brazilian economy. In addition, a quantile regression technique is used to construct density forecasts and generate probability density functions of future economic activity. Finally, a risk analysis is conducted within this set-up in order to compute conditional probabilities of the growth rate of the economy to be above/below a given scenario, which might be useful for both academics and policymakers' concerns.

JEL classifications: C53, E32, G10, G17
Keywords: Financial conditions index, Forecasting economic activity

[*] The opinions expressed in this publication are those of the authors and do not reflect the views of CEMLA, the EDF group, the Inter-American Development Bank or the Central Bank of Brazil. This research was undertaken within the framework of CEMLA's Joint Research Program 2016 coordinated by the Central Bank of Brazil. The authors gratefully acknowledge advice and technical assistance provided by the Financial Stability and Development Group of the Inter-American Development Bank in the process of writing this document. We are especially grateful for the helpful comments and suggestions given by Claudia Ramírez, Jorge Jaramillo, Pablo Guerrón-Quintana and Roberto Chang. We also benefited from comments and suggestions made by seminar participants in the CEMLA Joint Research 2016 Monetary Policy and Financial Conditions' Workshop at CEMLA Headquarters (Mexico City) and Workshop at IADB Headquarters (Washington, DC). Areosa and Gaglianone gratefully acknowledge the support of the IDB Network on Stability and Financial Development (SFD). Any remaining errors are ours.

Gaglianone: Research Department, Central Bank of Brazil; email: wagner.gaglianone@bcb.gov.br. Areosa: Investor Relations and Special Students Department, Central Bank of Brazil and Department of Economics, PUC-Rio, Brazil; email: waldyr.dutra@bcb.gov.br.

1 Introduction

Financial conditions have an important influence on business cycles, reflecting not only the current economic situation, but also market expectations of 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 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.

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 for the transmission of shocks. For example, the large corporate bond market in the United States and its expansion 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 (e.g., financial conditions that influence investment may be less important in periods of large excess capacity).

In this paper, we define the Financial Conditions Indicator (FCI) as an aggregate measure of financial conditions in the economy. This work aims to construct an FCI for Brazil.[1] The main idea is to build the FCI such that it embodies information on 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 cannot be obtained directly, such as risk aversion. An FCI thus 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.

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 in 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) empha-

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

sized, the period of near-zero short-term interest rates during the contraction phase of the Great Depression of 1929 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 for assessing the implications for the real economy of financial market developments. Consequently, FCIs can be useful in forecasting economic activity, making them useful for policymakers, particularly in relation to the definition of monetary or fiscal policy.[2]

The importance to the real economy of a well-functioning financial system is highlighted by 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, more directly affecting small businesses dependent on bank loans.[4] The decrease in credit supply ultimately affects investment, stocks and the economy as a whole.[5]

After the 2008 subprime crisis, there was a proliferation of indexes that sought 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

[2]See Kliesen et al. (2012) for a good discussion of financial stress indexes and financial conditions indicators.

[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).

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]

(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.

Here, we use factor analysis (FA) and 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. A historical decomposition of the Brazilian financial conditions reveals the relative importance of selected variables used in the construction of the FCI for the 2004-2016 period.

The Brazilian FCI is also compared to domestic economic activity proxies, showing that the financial conditions indeed Granger-cause the growth rates of the economy (the reverse causality is not supported by the data), in which shocks originating within the financial system impact the real economy. This statistical relationship is further explored in the construction of an econometric model used to generate density fore-

[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 a light weighted 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 data frequency, 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.

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

casts for economic activity based on the lagged FCI. As a result, we provide a tractable framework for risk analysis regarding future prospects of economic activity.

The next section details the methodology used in the construction of the FCI for Brazil, explaining each step of its construction. Section 3 presents the FCI and evaluates its properties. Section 4 concludes. Graphs and tables of the raw data are shown in the Appendix A.

2 Methodology

Brave and Butters (2011) constructed 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 bonds, 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 denote 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) investigated predictive ability of financial conditions indexes for the United States 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).

Next, we describe our data and the proposed methodology to build the FCI inspired by the approaches of Brave and Butters (2011) and Aramonte et al. (2013).

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 by, among others, the following features (see Pereira da Silva et al. (2012) and IMF-FSSA (2012) for further details):

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

- The real estate credit market has been one of the most dynamic sectors of the 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

[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."*

comparison to developed countries;

- In respect to financial deepening,[12] *Brazil contributed only 1.63% to global financial depth in 2009,*[13] *in sharp contrast to the United States (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 have access to a large and diversified domestic funding base;

- The Brazilian system of payments and settlements exhibits high compliance with 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 select (*ad hoc*) a set of 26 time series, which are listed in Table 1 (see Appendix A for further details). It is worth mentioning that this set of variables, of course, should

[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.

[13]Brazilian financial system is yet distant from financially-deep countries. Indeed, many emerging markets are still in the process of developing well-functioning financial systems (e.g., characterized by sound legal institutions and adequate property rights). Such limitations restrain the assets supply in local capital markets and limit the development of liquid financial markets. Although shrinking in recent years, the disparity in the degree of financial depth between emerging markets and advanced economies is still considerable (by the end of 2009, emerging markets accounted for roughly 40% of global GDP, whereas their contribution to financial depth was less than 20% that of advanced economies). This way, the Brazilian FCI's importance in economic activity (as documented in the following sections of this paper) is likely not driven by the building-up of the financial sector, although this channel might play a role in the future with a stronger pace for the Brazilian financial system deepening process.

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. The dataset covers the period from April 2003 to June 2016 (159 observations). The data sources are the Banco Central do Brasil, Bloomberg, BM&FBovespa, Ipeadata and Yahoo!Finance.

Table 1 - Selected Variables

Groups of variables	Time Series
1 - Opportunity cost	Swap Pré X DI (1 year and 5 years)
	Slope of the term structure of interest rates
	CDS Brazil
	Nonearmarked credit operations outstanding[1]
2 - Banking credit	Non-Performing Loans, Loan-to-Deposit Ratio
	Return on Equity
	Regulatory Capital to Risk-Weighted Assets
3 - Monetary aggregates[1]	Monetary base
	Demand deposits
	Money supply (M1, M2, M3 and 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

Note: [1] Series in real terms.

2.2 Main Steps to Build the FCI

We propose the following steps to construct the FCI:

1. *Series transformations*: The interest rate series (Selic and Swaps) 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), as well as the free credit series, are all seasonally adjusted (X12 filter) and deflated by IPCA. In addition, all non-stationary series, according to the ADF test and 5% significance level, are first-differenced (or second-differenced, if necessary) in order to end up with a group of stationary series.

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. Banbura et al. (2012, p.18) listed several papers which follow this same type of solution.

3. *Normalization*: In order 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 variance equal to one.

4. *Purged series*: We regress each *z-score* onto a set of macro variables (IPCA inflation and two lags of both economic activity proxies, as measured by the growth rate of

the seasonally adjusted IBC-BR or industrial production) and collect the residual series to be used as the *z-score* "purged" time series.

5. *Variable selection using Granger causality*: We drop from the set of variables (considered in the previous step) those that do not Granger-cause the economic activity proxy (5% significance).

6. *Aggregation*: Finally, the FCI is simply defined as a weighted average of the *z-scores*. This way, all the methodological discussion hereafter relies on the choice of appropriate weights (or loadings). Among the several possibilities suggested in the literature (e.g., equal weights; economic activity-driven weights; weights based on principal component analysis - PCA[14]), we adopt the factor analysis (FA) approach.[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 would heavily depend on the selection of series that compose the dataset (and how well balanced that dataset is in regard to the key features, shocks and tendencies of the financial system).

[14]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).

[15]Factor Analysis (FA) and Principal Components Analysis (PCA) are similar statistical techniques in the sense that both generate linear combinations of the original series. However, PCA is used to retain the maximum amount of information from data (in terms of total variation), whereas FA accounts for common variance. Thus, FA is often employed to build latent variables (or factors), while PCA is generally used in data reduction setups. Since our goal here is to build an aggregate index that reflects common movements in the financial system, we choose to extract factors from data.

In the second case, the economic activity-driven weights can be computed from impulse-response functions (IRF) of a Vector Autoregression (VAR) model, such that the FCI exhibits some (lagged) correlation with economic activity. Regarding the third route, the idea is to define the FCI as the first principal component of the base-variables.

Our FCI is based on the factor analysis methodology, by using the "principal factors" as the factor method and the "ordinary correlation" as covariance analysis. The idea is to obtain a vector of loadings that maximize the cumulative communality using an amount of n factors. Each retained indicator of financial conditions, y_{it} , can be decomposed into a common component and an idiosyncratic component: $y_{it} = \Lambda_i F_t + \varepsilon_{it}$.

The common component captures the bulk of the covariation between y_{it} and the other indicators, whereas the idiosyncratic term is assumed to affect only y_{it}. Thus, it is simply a scaled common factor, F_t , which is estimated using the entire set of financial indicators. The FCI is defined to be this common factor. We adopt a parsimonious model with a single factor ($n = 1$), since alternative models (with more variables or more factors), in general, deliver estimations with higher uniqueness and lower communality (in the additional variables and/or factors) in respect to the single-factor model.[16] Table 2 summarizes the loadings to build the FCI based on 5 variables (i.e., purged *z-scores* that survived the Granger causality test), hereafter simply called FCI, as well as the loadings for an alternative indicator based on 9 variables (FCI*).

[16]The number of factors here is set to one following, for instance, the parsimonious approach of Hatzius et al. (2010), which uses a single-factor model after taking into account the minimized sum of squared residuals (equivalently the maximized average R^2) and properly removing the business cycle effect from the original series. Nonetheless, there are many alternative factor selection tools available in the literature, such as the ones proposed by Bai and Ng (2002) or Alessi, Barigozzi and Capasso (2010).

Table 2 - Factor Model loadings: FCI and alternative indicator (FCI*)

Variable	Transform	Loadings	
		FCI	FCI*
Loan-to-Deposit ratio	Growth	-0.023	0.110
Ibovespa	Growth	0.787	0.786
Dow Jones	Growth	0.731	0.716
Real effective exchange rate	Growth	-0.666	-0.650
VIX	Level	-0.405	-0.397
Monetary base	Growth		0.040
Money supply (M1)	Growth		-0.025
Money supply (M2)	Growth		-0.316
Embi+BR	Level		0.063

Note: The variation explained by the factor is 47% in the FCI and 26% in the FCI*, which are computed from the eigenvalues obtained from the solution of each factor's linear combination as explained in Jolliffe (2002).

3 Results

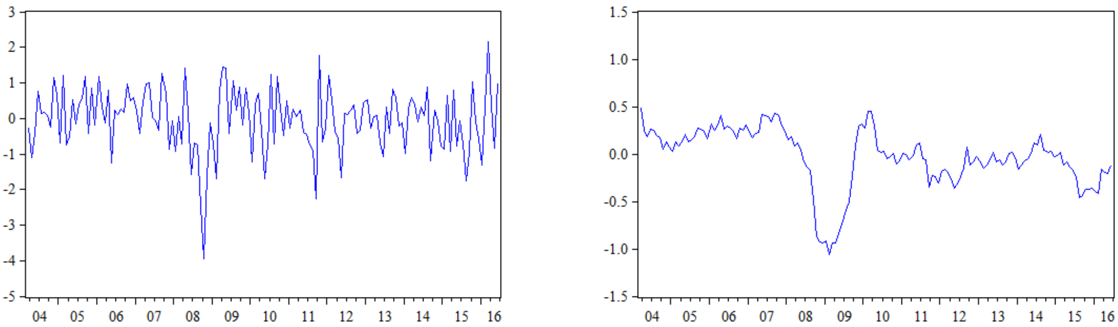
The FCI for Brazil is presented in Figure 1.[17] Note that due to the "normalization" step, it has zero mean. Those periods in which the FCI is above the zero line indicate positive financial shocks in the Brazilian economy (i.e., better financial conditions) and, reversely, periods such that the FCI is negative suggest tighter financial conditions. Note that the FCI indicates worse financial conditions with the aftermath of the global crisis in 2008 (in comparison to the historical pattern observed along 2003-2007).[18]

[17]We also computed the 12-month accumulated FCI in order to smooth the original monthly FCI. It is an additional way of presenting the results, in which one can better visualize the FCI dynamics accumulated through time and compare it, for instance, to the time evolution of the output gap or other relevant macro variable.

[18]Figure C1 (in Appendix C) presents a comparison of the FCI with three alternative financial conditions indicators based on: (i) equal weights of the purged *z-scores* that survived the GC test (FCI^{EW}); (ii) first principal component (FCI^{PC1}); and (iii) a single-factor model using 9 variables (FCI*).

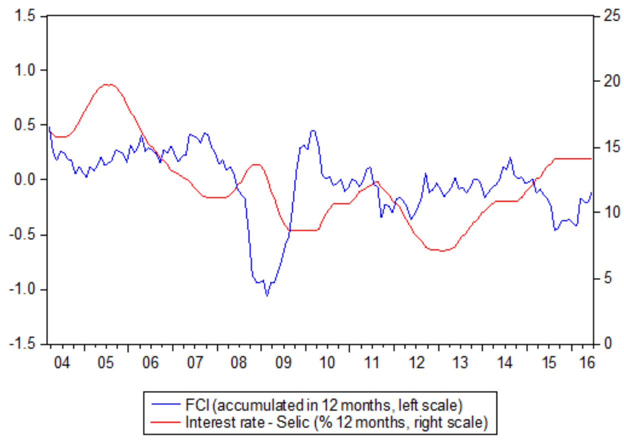
Figure 1 - Financial Conditions Indicator (FCI) for Brazil

(a) Monthly FCI | (b) FCI Accumulated in 12 Months



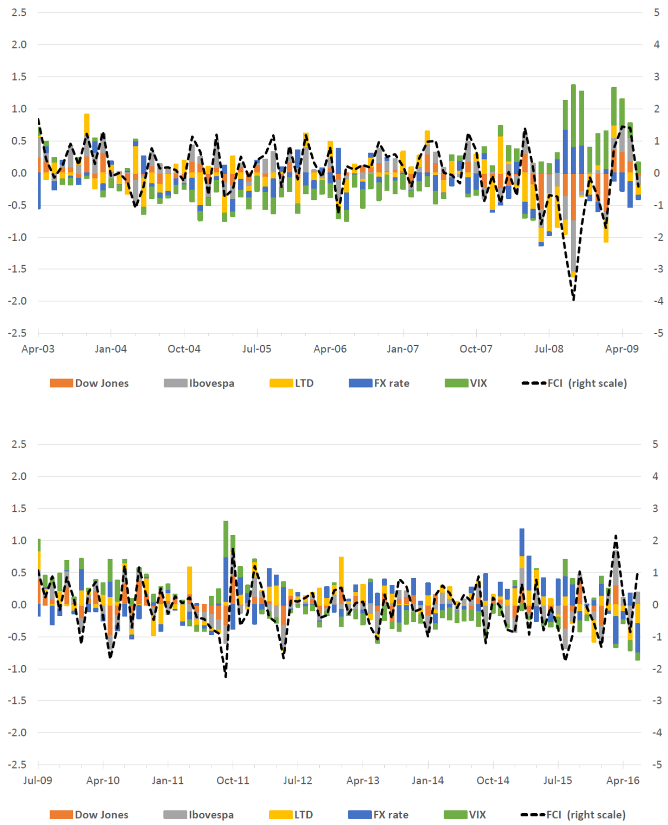
The comparison of the FCI, accumulated in 12 months, with the monetary policy interest rate (Selic) is shown in Figure 2. The FCI exhibits a positive correlation of 0.20 with the Selic, confirming that the interest rate is a key variable for the financial system, but does not account for the whole story about financial conditions. In other words, the FCI embodies a much broader information set, when compared to the basic interest rate series, containing information from distinct markets and different aspects of the economy and the financial system that the interest rate cannot cover alone.

Figure 2 - FCI Accumulated in 12 Months and the Selic Interest Rate



In Figure 3 we show the decomposition of FCI by variable to better understand the driving-forces behind the FCI's dynamics.

Figure 3 - FCI Decomposition by Variables

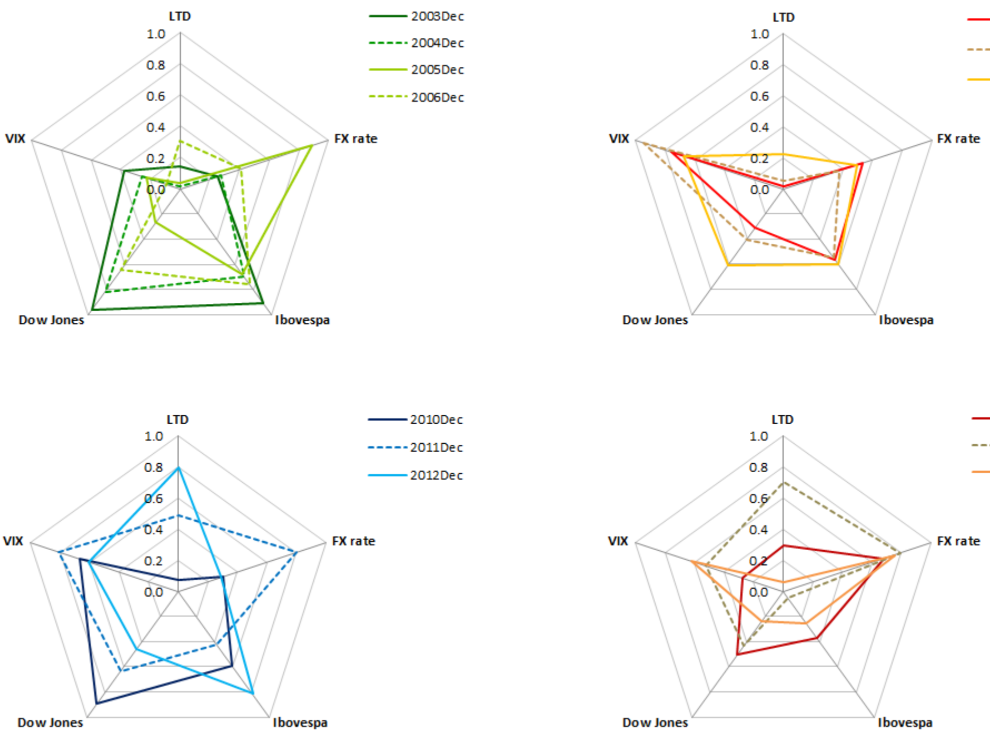


The results presented in Figure 3 can further be interpreted in terms of static comparisons. In other words, we next build a "map of contributions" to the FCI in selected periods. To do so, we first compute the empirical (unconditional) sample quantiles of the referred variables, along the whole considered sample. Next, we select a few periods (December of each year) and calculate the respective quantile level that corresponds to each observation. Then, for the selected periods, we plot the quantile level of the referred variable and compare it with the quantile levels obtained from the four other variables.

One of the advantages of such approach is to deal with a standardized measure (zero-one interval) which is comparable across the distinct series and periods. The results are presented in Figure 4. Note the "shrinking" evolution of the curves in the upper-left graph of Figure 4 (excepting the FX rate) along the 2003-2005 period, in line with the absence of significant financial shocks, as suggested by Figure 1. On the upper-right graph notice the 2008 global crisis, translated here by the sharp increase in the VIX indicator (as well as by the lower quantiles of LTD and the FX rate), reflecting worse financial conditions in respect to the historical pattern.

In contrast, along the 2010-2012 period (lower-left graph), note the relatively higher quantile levels obtained for LTD and the stock market indexes in the U.S. and Brazil, in line with some financial recovery after the 2008 crisis. Regarding the most recent period (lower-right graph), note the relatively moderate values for risk aversion (proxied here by the VIX), the LTD and the stock markets; coupled with a relatively higher FX rate (i.e., depreciated Real in respect to the U.S. Dollar).

Figure 4 - Map of Group Contributions

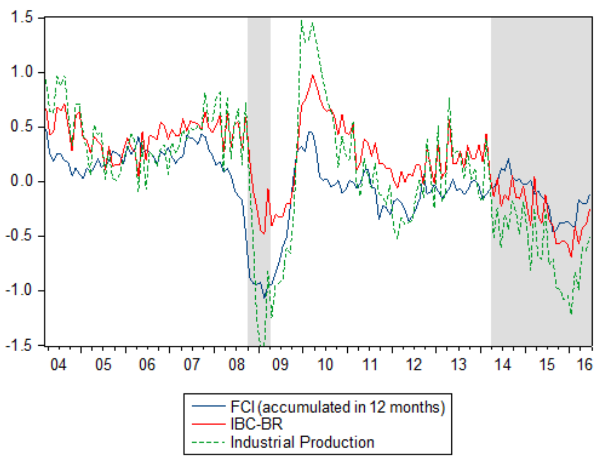


3.1 Assessing the FCI

We now compare the FCI with the growth rates of the seasonally adjusted economic activity proxies (IBC-BR or industrial production). 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). The results are presented in Figure 5.

It is worth mentioning that the 2008/2009 crisis first caused a deterioration of overall financial conditions (from the beginning of 2008) and, then, only some months later, did the pace of economic activity experience a negative impact (by the end of 2008). 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 in our sample we deal with very few recession episodes, notice (from a visual inspection in Figure 5) that the sharp drop in the FCI observed in the beginning of 2008 anticipates the recession periods of 2008-2009 (as well as the respective economic activity drops) by some months.

Figure 5 - FCI and Economic Activity Dynamics



Note: Gray vertical bars display the recession periods

according to the most recent report of CODACE (as of October 2016).

Table 3 - Contemporaneous and Lagged Correlations (leads and lags in months)

	IBC-BR(t)	Ind. Prod.(t)
FCI(t+6)	0.179	0.174
FCI(t+4)	0.324	0.368
FCI(t+2)	0.492	0.562
FCI(t+1)	0.565	0.640
FCI(t)	0.626	0.701
FCI(t-1)	0.676	**0.749**
FCI(t-2)	**0.680**	0.742
FCI(t-4)	0.611	0.621
FCI(t-6)	0.427	0.384

Table 4 - Granger Causality Test (p-values)

	Null Hypothesis			
Number of	FCI		IBC-BR	Ind. Prod.
lags used	does not GC	does not GC	does not GC	does not GC
in the test	IBC-BR	Ind. Prod.	FCI	FCI
2	0.0000	0.0000	0.135	0.112
3	0.0000	0.0000	0.449	0.338
4	0.0000	0.0000	0.679	0.520
5	0.0000	0.0000	0.869	0.695
6	0.0000	0.0000	0.818	0.878
7	0.0000	0.0000	0.770	0.885
8	0.0000	0.0000	0.902	0.960

In order to look for contemporaneous (or lagged) common movements, we next calculate the sample correlations between the FCI and the growth rates of the Brazilian economy. The positive signs obtained from correlations between the lagged FCI and the growth rates suggest that financial and business cycles might indeed not be synchronized in Brazil. 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 bold in Table 3) between the FCI and the economic proxies are obtained for one or two lags (months) of the FCI. These results, although based on unconditional calculations, suggest that the selected financial conditions indicator might anticipate the dynamics of the economy. Nonetheless, a more formal investigation to check these preliminary results is provided in Table 4 based on Granger causality tests.

First, note that the FCI Granger-causes (GC) the growth rate of both economic activity proxies. Moreover, the GC tests also suggest the existence of no causality in the opposite direction, indicating that financial shocks impact the real economy (a few months later) but the reverse does not hold.

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

$$y_t = \alpha + \beta FCI_{t-1} + \varepsilon_t, \tag{1}$$

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 either with heteroskedasticity-consistent standard errors or with the local-to-unity asymptotics procedure of Campbell and Yogo (2006).[19]

In our case, we study the multi-horizon step-ahead predictive power of FCI in respect to our proxy for economic growth y_t (based on IBC-BR or industrial production). Our predictive regression is the following:[20]

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 FCI_{t-h} + \beta_3 z_{t-h} + \varepsilon_t, \tag{2}$$

where h is the (monthly) forecast horizon, and the set of regressors, besides the

[19] In fact, Aramonte et al. (2013) assumed that the 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.

[20] Note that equations (1) and (2) suffer from the generated regressor problem (Pagan, 1984). Possible solutions (e.g., covariance matrix corrections) are suggested in Murphy and Topel (1985) and Hausman (2001). Here, we implicitly assume that the sampling error due to the FCI construction is negligible due to the relatively large sample size (roughly 160 observations). Moreover, the main focus is not on inference but on out-of-sample forecasting of economic activity.

intercept, now includes the lagged variable y_{t-1} (to account for autoregressive dynamics) and a control variable z_{t-h} (e.g., dummy for the 2008 crisis periods, which turns out to be not statistically significant in our regressions). 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).[21] The estimation results for a set of monthly forecast horizons h are presented in Tables 5-6.[22] Despite the Granger causality tests shown in Table 4, we also perform endogeneity tests to check for the (possible) need for instrumental variables (recall that if endogeneity is present, then, OLS estimates will be biased and inconsistent).[23]

Note that (in both economic proxies) the autoregressive coefficient is statistically significant (at 5%) for all horizons, and increases as long as the horizon rises (i.e., between horizons 2 and 6). At the same time, the coefficient associated with the FCI is also significant (but only for horizons of one and two months), and its magnitude decreases as long as the horizon increases. The coefficient for the dummy variable of the 2008 crisis is not significant in all cases and such variable was removed from the final regressions. Also, note that the LM test indicates no residual autocorrelation and the Hausman test suggests no endogeneity regarding the FCI.

[21] 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.

[22] In Appendix B, the regression estimates based on the alternative indicator FCI* are provided as a robustness check. The results are quite similar compared to those shown in Tables 5-6.

[23] 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 equation (2) 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 5 - Regression Estimates (IBC-BR)

Regressors	h=1	h=2	h=3	h=6	h=9	h=12
	Dependent Variable: IBC-BR (t)					
Constant	0.208	0.201	0.168	0.146	0.145	0.148
	(0)	(0.001)	(0.042)	(0.18)	(0.146)	(0.168)
AR(1)	0.775	0.777	0.832	0.865	0.858	0.868
	(0)	(0)	(0)	(0)	(0)	(0)
FCI (t-h)	0.566	0.485	0.176	-0.023	0.160	0.051
	(0)	(0)	(0.266)	(0.88)	(0.293)	(0.786)
R-squared	0.771	0.762	0.748	0.740	0.745	0.744
Adjusted R-squared	0.768	0.759	0.745	0.736	0.742	0.740
Residual autocorrelation LM test (p-value)						
1lag	0.000	0.000	0.000	0.000	0.000	0.000
4 lags	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test1(p-value)	0.293	0.576	0.407	0.997	0.894	0.430
Hausman test2 (p-value)	0.313	0.466	0.500	0.867	0.217	0.773

Notes: Sample May2004-Jun2016. P-values in parentheses.

Newey and West (1987)'s HAC covariance matrix of residuals.

The null hypothesis of the Hausman test assumes no endogeneity regarding FCI.

The Hausman test1 employs the vector of instruments $z_t^1 = [\Delta \ln(Embi_{t-h-i})]'$,

whereas the test2 is based on $z_t^2 = [\Delta \ln(CDS_{t-h-i})]'$; for $i = \{0; 1; 2\}$.

Table 6 - Regression Estimates (Industrial Production)

Regressors	h=1	h=2	h=3	h=6	h=9	h=12
	Dependent Variable: Ind.Production (t)					
Constant	0.080	0.071	0.016	-0.033	-0.037	-0.028
	(0.297)	(0.37)	(0.892)	(0.849)	(0.825)	(0.869)
AR(1)	0.687	0.687	0.787	0.848	0.841	0.843
	(0)	(0)	(0)	(0)	(0)	(0)
FCI (t-h)	1.225	1.142	0.443	-0.053	0.130	-0.067
	(0)	(0)	(0.186)	(0.828)	(0.629)	(0.835)
R-squared	0.768	0.758	0.726	0.713	0.712	0.712
Adjusted R-squared	0.765	0.754	0.722	0.709	0.708	0.707
Residual autocorrelation LM test (p-value)						
1lag	0.000	0.000	0.000	0.001	0.001	0.001
4 lags	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test1(p-value)	0.333	0.918	0.424	0.714	0.496	0.777
Hausman test2 (p-value)	0.363	0.732	0.439	0.998	0.736	0.616

Notes: Sample May2004-Jun2016. P-values in parentheses.

Newey and West (1987)'s HAC covariance matrix of residuals.

The null hypothesis of the Hausman test assumes no endogeneity regarding FCI.

The Hausman test1 employs the vector of instruments $z_t^1 = [\Delta \ln(Embi_{t-h-i})]'$,

whereas the test2 is based on $z_t^2 = [\Delta \ln(CDS_{t-h-i})]'$; for $i = \{0; 1; 2\}$.

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 observed economic activity growth rate, that is: $\widehat{y}^{M1}_{t+h} = y_t$. The second forecast (M2) is based on the AR(1) regression, such that $\widehat{y}^{M2}_{t+h} = \widehat{\alpha} + \widehat{\beta} y_t$. In turn, forecast from model M3 is given by $\widehat{y}^{M3}_{t+h} = \widehat{\alpha} + \widehat{\beta}_1 y_t + \widehat{\beta}_2 FCI_{t-p}$, where the lag p ranges from zero to twelve months ($p = 0, ..., 12$). For instance, we label "M3 lag 5" the M3 model with FCI_{t-5} as regressor. The proxies for economic activity are again based on the IBC-BR or industrial production series.

Forecasts are generated here both by a recursive scheme (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 April 2004 and (initially) ends at June 2011, 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 July 2011 through June 2016 (60 observations). The results of the exercise are summarized in Tables 7-8 in terms of the mean squared forecast error (MSFE) loss function.

Note from Table 7 (Panel A) that forecasts from model M3 (lag 4) show the best performance for the one-month-ahead horizon, suggesting that a financial conditions indicator might indeed have some information content about future economic activity. For longer horizons, however, the random walk (M1) performed relatively better than the competing models. Also, note that MSFEs from the rolling window scheme are, overall, lower than the respective figures from the expanding sample scheme. The statistical significance of the MSFE gains are verified by the Clark and West (2006, 2007) test for nested models, in the case of expanding sample, and the predictive ability test of Giacomini and White (2006), in the case of rolling window estimation. The benchmark model in both tests is the random walk (M1). The results indicate a rejection of the null hypothesis of equal predictive ability (blue cells) in very few cases, suggesting the difficulty on statistically beating the random walk. Nonetheless, the forecast using the FCI (model M3, lag4) is statistically better than the random walk in Panel A for $h = 1$. Similar results are found in Table 8 by using the industrial production growth rate series as proxy.[24]

In Appendix C, we present additional results for the out-of-sample forecast evaluation using alternative FCIs. We construct forecasts from additional models M4, M5 and M6 by substituting the FCI by its alternative indicators FCI^{EW}, FCI^{PC1} and FCI*, respectively. The Diebold and Mariano (1995) test for non-nested models is used for expanding sample and the Giacomini and White (2006) test in the case of rolling window estimation. In both tests, the benchmark model is M3 lag i, which is statistically compared (pairwise) with model M4 (or M5 or M6) also with lag i, for each $i = 0, ..., 12$.

[24] One way to check whether the FCI improves the predictive content of real variables only during selected episodes of the investigated sample period is to apply the methodology of Giacomini and Rossi (2010), which compares the out-of-sample forecasting performance of two competing models in the presence of possible instabilities. The main idea is to use a measure of local forecasting performance for the two competing models and to investigate its stability over time by means of statistical tests.

Overall, the results indicate that the alternative FCIs only in some cases provide better forecasts compared to the FCI-based model (e.g., in general, when using expanding sample estimation and with lags higher than 6 months). Moreover, the alternative FCIs quite often do not provide superior forecasts (compared to the FCI) for very short horizons and using a few (or no) lags, which are exactly the cases where the FCI-based forecasts are statistically better than the random walk and the AR(1) forecasts as shown in Tables 7-8.

Table 7 - 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	0.038	0.038	0.039	0.040	0.039	0.038	**0.037**	0.037	0.038	0.038	0.038	0.039	0.040	0.040	0.041
	-	(0.047)	(0.004)	(0.004)	(0.005)	(0.006)	(0.017)	(0.031)	(0.043)	(0.086)	(0.078)	(0.108)	(0.12)	(0.113)	(0.117)
2	**0.035**	0.039	0.045	0.044	0.042	0.037	0.037	0.038	0.038	0.039	0.040	0.041	0.042	0.043	0.043
	-	(0.238)	(0.029)	(0.035)	(0.043)	(0.088)	(0.256)	(0.343)	(0.505)	(0.5)	(0.494)	(0.529)	(0.499)	(0.472)	(0.415)
3	**0.027**	0.037	0.054	0.054	0.042	0.035	0.033	0.034	0.035	0.036	0.038	0.041	0.043	0.045	0.046
	-	(0.988)	(0.487)	(0.517)	(0.629)	(0.852)	(0.849)	(0.744)	(0.787)	(0.81)	(0.858)	(0.862)	(0.866)	(0.907)	(0.938)
4	**0.053**	0.071	0.097	0.090	0.076	0.068	0.064	0.066	0.068	0.070	0.074	0.078	0.082	0.085	0.088
	-	(0.328)	(0.083)	(0.093)	(0.124)	(0.213)	(0.453)	(0.545)	(0.59)	(0.605)	(0.587)	(0.585)	(0.539)	(0.495)	(0.463)
5	**0.053**	0.083	0.113	0.102	0.087	0.073	0.069	0.071	0.075	0.079	0.085	0.090	0.096	0.101	0.103
	-	(0.711)	(0.41)	(0.414)	(0.483)	(0.608)	(0.721)	(0.757)	(0.771)	(0.763)	(0.753)	(0.737)	(0.72)	(0.709)	(0.702)
6	**0.056**	0.106	0.145	0.135	0.108	0.091	0.081	0.084	0.090	0.096	0.103	0.110	0.118	0.124	0.127
	-	(0.903)	(0.824)	(0.818)	(0.812)	(0.817)	(0.793)	(0.8)	(0.816)	(0.812)	(0.807)	(0.807)	(0.813)	(0.828)	(0.829)
7	**0.065**	0.141	0.192	0.174	0.148	0.121	0.110	0.115	0.121	0.129	0.138	0.147	0.156	0.162	0.168
	-	(1)	(0.824)	(0.825)	(0.865)	(0.932)	(0.976)	(0.978)	(0.969)	(0.987)	(1)	(0.994)	(0.997)	(0.995)	(0.998)
8	**0.068**	0.157	0.205	0.190	0.151	0.126	0.117	0.123	0.134	0.143	0.154	0.164	0.173	0.182	0.186
	-	(0.837)	(0.873)	(0.897)	(0.926)	(0.948)	(0.963)	(0.942)	(0.924)	(0.931)	(0.924)	(0.9)	(0.895)	(0.88)	(0.874)
9	**0.080**	0.188	0.234	0.211	0.174	0.152	0.142	0.152	0.163	0.173	0.187	0.196	0.206	0.213	0.220
	-	(0.884)	(0.942)	(0.968)	(0.973)	(0.936)	(0.94)	(0.912)	(0.914)	(0.928)	(0.903)	(0.908)	(0.894)	(0.886)	(0.883)
10	**0.079**	0.227	0.269	0.244	0.207	0.179	0.173	0.183	0.193	0.206	0.217	0.228	0.238	0.248	0.254
	-	(0.671)	(0.758)	(0.799)	(0.8)	(0.776)	(0.746)	(0.722)	(0.714)	(0.691)	(0.686)	(0.671)	(0.663)	(0.652)	(0.65)
11	**0.093**	0.247	0.281	0.260	0.223	0.205	0.200	0.206	0.220	0.229	0.240	0.249	0.259	0.266	0.274
	-	(0.812)	(0.899)	(0.923)	(0.937)	(0.886)	(0.876)	(0.85)	(0.802)	(0.809)	(0.781)	(0.772)	(0.762)	(0.753)	(0.724)
12	**0.113**	0.271	0.304	0.285	0.263	0.246	0.237	0.245	0.252	0.258	0.269	0.275	0.284	0.291	0.300
	-	(0.868)	(0.8)	(0.778)	(0.789)	(0.8)	(0.798)	(0.858)	(0.843)	(0.873)	(0.889)	(0.901)	(0.915)	(0.956)	(0.99)

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	0.038	0.039	0.039	0.040	0.038	**0.035**	0.042	0.042	0.038	0.044	0.040	0.040	0.042	0.039	0.041
	-	(0.662)	(0.882)	(0.783)	(0.973)	(0.534)	(0.258)	(0.235)	(0.9)	(0.182)	(0.594)	(0.485)	(0.362)	(0.69)	(0.445)
2	**0.035**	0.038	0.046	0.043	0.036	0.037	0.043	0.038	0.039	0.040	0.038	0.040	0.039	0.040	0.039
	-	(0.546)	(0.175)	(0.27)	(0.925)	(0.609)	(0.063)	(0.374)	(0.208)	(0.208)	(0.48)	(0.286)	(0.405)	(0.367)	(0.433)
3	**0.027**	0.033	0.051	0.044	0.031	0.031	0.032	0.031	0.030	0.031	0.031	0.032	0.034	0.034	0.035
	-	(0.11)	(0.001)	(0.001)	(0.229)	(0.186)	(0.094)	(0.131)	(0.202)	(0.166)	(0.187)	(0.156)	(0.109)	(0.101)	(0.07)
4	**0.053**	0.061	0.092	0.074	0.056	0.054	0.060	0.058	0.058	0.060	0.060	0.062	0.063	0.065	0.068
	-	(0.421)	(0.112)	(0.183)	(0.756)	(0.839)	(0.314)	(0.453)	(0.497)	(0.426)	(0.459)	(0.378)	(0.359)	(0.304)	(0.242)
5	0.053	0.067	0.102	0.076	0.055	**0.052**	0.055	0.055	0.056	0.058	0.061	0.063	0.067	0.071	0.074
	-	(0.184)	(0.013)	(0.014)	(0.703)	(0.962)	(0.797)	(0.786)	(0.663)	(0.578)	(0.436)	(0.33)	(0.231)	(0.154)	(0.11)
6	0.056	0.083	0.115	0.089	0.056	**0.053**	0.054	0.057	0.061	0.064	0.069	0.074	0.080	0.087	0.093
	-	(0.177)	(0.025)	(0.029)	(0.977)	(0.755)	(0.84)	(0.914)	(0.664)	(0.526)	(0.355)	(0.251)	(0.18)	(0.133)	(0.106)
7	**0.065**	0.107	0.140	0.099	0.071	0.066	0.067	0.073	0.079	0.084	0.092	0.099	0.108	0.117	0.126
	-	(0.172)	(0.055)	(0.102)	(0.664)	(0.915)	(0.845)	(0.518)	(0.367)	(0.271)	(0.189)	(0.14)	(0.109)	(0.09)	(0.075)
8	0.068	0.127	0.138	0.099	0.064	**0.062**	0.064	0.072	0.083	0.091	0.102	0.113	0.123	0.134	0.143
	-	(0.143)	(0.029)	(0.059)	(0.747)	(0.588)	(0.74)	(0.754)	(0.409)	(0.279)	(0.184)	(0.135)	(0.109)	(0.091)	(0.081)
9	0.080	0.155	0.156	0.108	**0.074**	0.076	0.077	0.093	0.105	0.114	0.129	0.140	0.153	0.164	0.176
	-	(0.168)	(0.075)	(0.176)	(0.601)	(0.748)	(0.827)	(0.523)	(0.324)	(0.241)	(0.174)	(0.145)	(0.122)	(0.109)	(0.094)
10	0.079	0.179	0.163	0.108	0.076	**0.073**	0.081	0.101	0.116	0.132	0.149	0.162	0.176	0.190	0.202
	-	(0.115)	(0.036)	(0.077)	(0.795)	(0.649)	(0.9)	(0.309)	(0.179)	(0.127)	(0.1)	(0.084)	(0.074)	(0.064)	(0.055)
11	0.093	0.206	0.170	0.122	**0.084**	0.093	0.101	0.121	0.144	0.158	0.175	0.189	0.202	0.216	0.230
	-	(0.169)	(0.116)	(0.29)	(0.606)	(0.997)	(0.756)	(0.404)	(0.26)	(0.214)	(0.178)	(0.156)	(0.138)	(0.123)	(0.106)
12	**0.113**	0.227	0.185	0.132	0.115	0.121	0.127	0.156	0.172	0.185	0.201	0.211	0.224	0.237	0.251
	-	(0.223)	(0.237)	(0.566)	(0.934)	(0.812)	(0.684)	(0.395)	(0.319)	(0.276)	(0.238)	(0.215)	(0.192)	(0.171)	(0.15)

Note: The minimum MSFE for each horizon (h) is marked in bold. In Panel A, the p-value of the equal predictive accuracy test of Clark and West (2007) for nested models is shown in parentheses. In Panel B, the p-value of the Giacomini and White (2006) test is shown in parentheses. Both panels use the MSFE loss and model M1 (RW) as the benchmark. Blue cells indicate a rejection of the test (p-value<0.05).

Table 8 - Out-of-Sample Forecast Evaluation (MSFE)

Panel A: Industrial Production (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	0.104	0.099	**0.092**	0.093	0.093	0.094	0.099	0.101	0.101	0.104	0.103	0.105	0.106	0.107	0.108
	-	(0.012)	(0.001)	(0.001)	(0.001)	(0.002)	(0.01)	(0.024)	(0.026)	(0.057)	(0.035)	(0.045)	(0.046)	(0.042)	(0.044)
2	0.101	0.100	0.110	0.104	0.098	**0.098**	0.103	0.104	0.107	0.108	0.110	0.114	0.116	0.119	0.118
	-	(0.057)	(0.002)	(0.002)	(0.004)	(0.037)	(0.228)	(0.239)	(0.291)	(0.255)	(0.218)	(0.222)	(0.205)	(0.197)	(0.164)
3	**0.082**	0.100	0.143	0.131	0.101	0.092	0.093	0.098	0.102	0.108	0.114	0.122	0.130	0.132	0.130
	-	(0.355)	(0.135)	(0.143)	(0.196)	(0.385)	(0.498)	(0.528)	(0.489)	(0.477)	(0.451)	(0.449)	(0.448)	(0.424)	(0.402)
4	**0.153**	0.177	0.218	0.197	0.169	0.167	0.173	0.180	0.189	0.198	0.209	0.222	0.230	0.233	0.233
	-	(0.118)	(0.007)	(0.009)	(0.034)	(0.143)	(0.309)	(0.304)	(0.295)	(0.289)	(0.271)	(0.271)	(0.247)	(0.225)	(0.207)
5	**0.151**	0.208	0.266	0.229	0.192	0.179	0.182	0.192	0.205	0.219	0.237	0.250	0.261	0.269	0.267
	-	(0.292)	(0.11)	(0.137)	(0.203)	(0.284)	(0.315)	(0.318)	(0.314)	(0.309)	(0.306)	(0.296)	(0.284)	(0.276)	(0.267)
6	**0.158**	0.264	0.328	0.289	0.229	0.213	0.212	0.227	0.246	0.266	0.286	0.301	0.318	0.325	0.324
	-	(0.408)	(0.309)	(0.307)	(0.317)	(0.315)	(0.306)	(0.309)	(0.316)	(0.32)	(0.316)	(0.313)	(0.311)	(0.314)	(0.314)
7	**0.194**	0.345	0.402	0.350	0.299	0.274	0.274	0.293	0.316	0.336	0.357	0.376	0.392	0.401	0.410
	-	(0.351)	(0.227)	(0.24)	(0.265)	(0.281)	(0.284)	(0.291)	(0.296)	(0.289)	(0.283)	(0.278)	(0.278)	(0.276)	(0.277)
8	**0.188**	0.397	0.434	0.389	0.319	0.293	0.294	0.317	0.345	0.368	0.391	0.410	0.427	0.444	0.442
	-	(0.514)	(0.455)	(0.422)	(0.377)	(0.344)	(0.334)	(0.346)	(0.35)	(0.348)	(0.348)	(0.354)	(0.356)	(0.361)	(0.365)
9	**0.223**	0.463	0.484	0.433	0.370	0.351	0.352	0.378	0.403	0.424	0.449	0.465	0.487	0.494	0.505
	-	(0.409)	(0.324)	(0.301)	(0.283)	(0.282)	(0.28)	(0.282)	(0.277)	(0.269)	(0.273)	(0.269)	(0.271)	(0.272)	(0.273)
10	**0.200**	0.541	0.554	0.503	0.436	0.405	0.414	0.437	0.461	0.485	0.508	0.529	0.546	0.565	0.577
	-	(0.702)	(0.609)	(0.553)	(0.518)	(0.509)	(0.508)	(0.507)	(0.499)	(0.506)	(0.506)	(0.509)	(0.511)	(0.516)	(0.517)
11	**0.252**	0.581	0.571	0.534	0.473	0.456	0.460	0.472	0.494	0.509	0.529	0.543	0.562	0.576	0.592
	-	(0.444)	(0.334)	(0.305)	(0.281)	(0.285)	(0.275)	(0.266)	(0.272)	(0.265)	(0.272)	(0.271)	(0.271)	(0.272)	(0.282)
12	**0.300**	0.613	0.592	0.564	0.536	0.513	0.508	0.516	0.525	0.534	0.549	0.561	0.576	0.591	0.607
	-	(0.245)	(0.153)	(0.143)	(0.139)	(0.133)	(0.124)	(0.127)	(0.119)	(0.121)	(0.123)	(0.121)	(0.121)	(0.124)	(0.128)

Panel B: Industrial Production (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	0.104	0.107	0.100	**0.095**	0.102	0.096	0.118	0.118	0.107	0.122	0.110	0.110	0.117	0.110	0.115
	-	(0.77)	(0.785)	(0.559)	(0.866)	(0.283)	(0.176)	(0.184)	(0.711)	(0.162)	(0.528)	(0.553)	(0.322)	(0.637)	(0.416)
2	0.101	0.105	0.125	0.107	**0.097**	0.110	0.125	0.110	0.114	0.113	0.107	0.113	0.111	0.113	0.105
	-	(0.758)	(0.296)	(0.733)	(0.623)	(0.395)	(0.121)	(0.393)	(0.308)	(0.373)	(0.672)	(0.437)	(0.541)	(0.508)	(0.821)
3	**0.082**	0.093	0.143	0.107	0.092	0.094	0.094	0.093	0.089	0.091	0.093	0.094	0.098	0.094	0.096
	-	(0.317)	(0.001)	(0.052)	(0.417)	(0.372)	(0.397)	(0.478)	(0.603)	(0.554)	(0.508)	(0.469)	(0.391)	(0.46)	(0.409)
4	**0.153**	0.160	0.209	0.156	0.157	0.161	0.177	0.168	0.165	0.171	0.169	0.176	0.171	0.174	0.182
	-	(0.817)	(0.289)	(0.945)	(0.903)	(0.758)	(0.436)	(0.63)	(0.716)	(0.617)	(0.658)	(0.563)	(0.632)	(0.592)	(0.489)
5	0.151	0.173	0.234	0.160	**0.139**	0.148	0.151	0.150	0.156	0.160	0.168	0.169	0.176	0.186	0.189
	-	(0.52)	(0.047)	(0.766)	(0.669)	(0.936)	(0.99)	(0.993)	(0.887)	(0.811)	(0.687)	(0.648)	(0.548)	(0.441)	(0.393)
6	0.158	0.204	0.245	0.169	**0.145**	0.147	0.151	0.158	0.166	0.176	0.184	0.195	0.208	0.218	0.229
	-	(0.37)	(0.08)	(0.766)	(0.695)	(0.75)	(0.843)	(1)	(0.859)	(0.715)	(0.605)	(0.484)	(0.377)	(0.304)	(0.25)
7	0.194	0.253	0.279	0.185	**0.170**	0.180	0.186	0.197	0.210	0.220	0.236	0.252	0.267	0.284	0.301
	-	(0.429)	(0.253)	(0.85)	(0.562)	(0.735)	(0.859)	(0.954)	(0.775)	(0.656)	(0.517)	(0.408)	(0.328)	(0.267)	(0.217)
8	0.188	0.290	0.268	0.176	**0.155**	0.166	0.174	0.194	0.216	0.234	0.257	0.276	0.297	0.318	0.331
	-	(0.293)	(0.214)	(0.786)	(0.4)	(0.595)	(0.77)	(0.9)	(0.646)	(0.493)	(0.363)	(0.28)	(0.223)	(0.182)	(0.162)
9	0.223	0.338	0.289	0.195	**0.182**	0.199	0.209	0.238	0.260	0.279	0.305	0.324	0.348	0.367	0.390
	-	(0.357)	(0.418)	(0.557)	(0.332)	(0.627)	(0.795)	(0.821)	(0.624)	(0.502)	(0.39)	(0.325)	(0.264)	(0.233)	(0.198)
10	0.200	0.379	0.297	0.198	**0.175**	0.192	0.221	0.258	0.286	0.315	0.341	0.365	0.389	0.414	0.436
	-	(0.176)	(0.147)	(0.947)	(0.528)	(0.838)	(0.694)	(0.388)	(0.264)	(0.192)	(0.145)	(0.113)	(0.093)	(0.075)	(0.061)
11	0.252	0.407	0.298	0.216	**0.189**	0.233	0.260	0.290	0.323	0.343	0.366	0.387	0.409	0.430	0.455
	-	(0.357)	(0.591)	(0.491)	(0.204)	(0.787)	(0.928)	(0.706)	(0.541)	(0.465)	(0.393)	(0.343)	(0.295)	(0.257)	(0.216)
12	0.300	0.421	0.306	**0.230**	0.250	0.284	0.303	0.338	0.355	0.371	0.390	0.404	0.423	0.443	0.466
	-	(0.511)	(0.952)	(0.288)	(0.53)	(0.874)	(0.975)	(0.771)	(0.691)	(0.628)	(0.559)	(0.512)	(0.458)	(0.407)	(0.354)

Note: The minimum MSFE for each horizon (h) is marked in bold. In Panel A, the p-value of the equal predictive accuracy test of Clark and West (2007) for nested models is shown in parentheses. In Panel B, the p-value of the Giacomini and White (2006) test is shown in parentheses. Both panels use the MSFE loss and model M1 (RW) as the benchmark. Blue cells indicate a rejection of the test (p-value<0.05).

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 the 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 several horizons. The density forecasts are generated by using a semiparametric approach based on quantile regression, as suggested by Gaglianone and Lima (2012).[25] By using standard quantile regression techniques (see Koenker, 2005), the conditional quantiles of y_{t+h} (which denotes the economic growth rate, 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

[25] The authors generate multi-step-ahead conditional density forecasts for the unemployment rate in the United States from (point) consensus forecasts and quantile regression.

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 crisis is considered in z_t.

The estimation sample ranges from April 2004 to June 2016 ($T = 147$ observations) and quantile regression (3) is estimated for horizons $h = 1, ..., 12$ months (in order to produce density forecasts up to June 2017) and on a discrete set of quantile levels $\tau = [0.01; 0.02; ...; 0.99]$. The one-month-ahead forecast is constructed by $\widehat{Q}_\tau(y_{t+1|t}) = \mathbf{X}_t'\widehat{\boldsymbol{\theta}}_{h=1}(\tau)$, for all $\tau \in [0.01; 0.02; ...; 0.99]$. 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, for instance, the Epanechnikov kernel, which is a weighting function that determines the shape of the bumps.

Note in Table 9 and Figure 6 the positive skewness in both densities along the second half of 2016, probably due to the asymmetric (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 rises (except for industrial production in June 2017).

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.[26] The results are presented in Table 10, in which the output growth rates computed from our density model are compared to selected year-over-year (yoy) growth rates. Of course, the results will heavily depend on the quality of the

[26]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 $(1 - \tau^*)$.

point forecast, since the location of the distribution is key for all estimated conditional densities (and the respective computation of probabilities). For comparison purposes, we also present the growth rates expected by the market agents surveyed by the Banco Central do Brasil.

It is worth mentioning that the density forecast setup used here for risk analysis is only 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 approach provides.

Table 9 - Descriptive Statistics of the PDFs (monthly % growth rates)

IBC-BR	Sep-16	Dec-16	Mar-17	Jun-17
Mean	-0.13	-0.06	0.01	0.11
Median	-0.15	-0.11	0.01	0.14
Std. Dev.	0.24	0.37	0.43	0.46
Skewness	1.30	0.82	0.14	-0.16
Kurtosis	6.12	3.77	2.02	1.53

Ind. Production	Sep-16	Dec-16	Mar-17	Jun-17
Mean	-0.33	-0.20	-0.07	0.07
Median	-0.31	-0.27	-0.04	0.10
Std. Dev.	0.37	0.56	0.65	0.62
Skewness	1.53	0.82	0.11	-0.08
Kurtosis	8.55	3.97	2.31	1.70

Figure 6 - Probability Density Functions (PDFs) for the

IBC-BR (left) and Industrial Production (right), monthly % growth rates

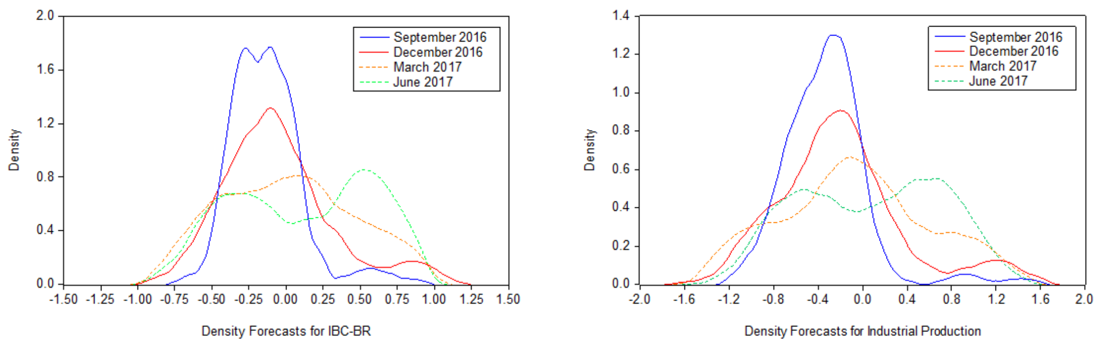


Table 10 - Point |Forecasts and Conditional Probabilities

IBC-BR

	Growth rates (% yoy) for 2016	Probability (%) of growth rate *< -2%*	Probability (%) of growth rate *< -4%*
Median (Focus) survey expectation *(as of 21 October 2016)*	-3.22%	-	-
Point forecasts from the QR model	-3.44%	85%	34%

Industrial Production

	Growth rates (% yoy) for 2016	Probability (%) of growth rate *< -4%*	Probability (%) of growth rate *< -8%*
Median (Focus) survey expectation *(as of 21 October 2016)*	-6.00%	-	-
Point forecasts from the QR model	-6.64%	89%	26%

Notes: Survey expectations are from the Focus dataset (as of 21 October 2016). Regarding the first table, since expectations for the IBC-BR are not available, we present (just for comparison purposes) the median survey-based expectations for the real GDP growth rate from the Focus survey.

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 are used to generate a single time series that summarizes this richer information set (when compared, for instance, to a single policy interest rate).

In this paper, we propose a novel methodology to construct the FCI, 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 reduced-form equation is employed to point forecast the growth rate of the Brazilian economy. Moreover, we use a quantile regression technique to construct density forecasts and generate probability density functions of future economic activity. A risk analysis is also conducted within this setup in order to compute conditional probabilities of the growth rate be above (or below) a given scenario.

References

[1] Alessi, L., M. Barigozzi and M. Capasso. 2010. "Improved Penalization for Determining the Number of Factors in Approximate Factor Models." *Statistics & Probability Letters* 80 (23-24): 1806-1813.

[2] Aramonte, S., S. Rosen and J. W. Schindler. 2013. "Assessing and Combining Financial Conditions Indexes." Finance and Economics Paper 2013-39. Washington, DC, United States: Board of Governors of the Federal Reserve System.

[3] Bai, J., and S. Ng. 2002. "Determining the Number of Factors in Approximate Factor Models." *Econometrica* 70(1): 191-221.

[4] Banbura, M., D. Giannone, M. Modugno and L. Reichlin. 2012. "Now-casting and the Real-time Data Flow." ECARES Working Paper 2012-026. Brussels, Belgium: European Center for Advanced Research in Economics and Statistics.

[5] Bates, J.M., and C. W. J. Granger. 1969. "The Combination of Forecasts." *Operations Research Quarterly* 20, 309-325.

[6] Beaton, K., R. Lalonde and C. Luu. 2009. "A Financial Conditions Index for the United States." Bank of Canada Discussion Paper 09-11. Ottawa, Canada: Bank of Canada.

[7] Bernanke, B.S. 1983. "Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression." *American Economic Review* 73(3): 257-276.

[8] Bernanke, B.S., and A. S. Blinder. 1992. "The Federal Funds Rate and the Channels of Monetary Transmission." *American Economic Review* 82(4): 901-921.

[9] Borio, C. 2011. "Rediscovering the Macroeconomic Roots of Financial Stability Policy: Journey, Challenges and a Way Forward." BIS Working Paper. 354. Basel, Switzerland: Bank for International Settlements. Available at: http://www.bis.org/publ/work354.pdf

[10] Brave, S. and A. Butters. 2011. "Monitoring Financial Stability: A Financial Conditions Index Approach." *Economic Perspectives* 1Q/2011, 22-43.

[11] Calomiris, C.W. and J. R. Mason. 2003. "Consequences of Bank Distress During the Great Depression." *American Economic Review* 93(3): 937-947.

[12] Campbell, J., and M. Yogo. 2006. "Efficient Tests of Stock Return Predictability." *Journal of Financial Economics* 81(1): 27-60.

[13] Campello, M., J. R. Graham, J.R. and C. R. Harvey. 2010. "The Real Effects of Financial Constraints: Evidence from a Financial Crisis." *Journal of Financial Economics* 97(3): 470-487.

[14] Carlson, M.A., K. F. Lewis and W. R. Nelson. 2012. "Using Policy Intervention to Identify Financial Stress." Finance and Economics Discussion Series: 2012-02. Washington, DC, United States: Federal Reserve Board. Available at: http://www.federalreserve.gov/pubs/feds/2012/201202/

[15] Chava, S. and A. Purnanandam. 2011. "The Effect of Banking Crisis on Bank-Dependent Borrowers." *Journal of Financial Economics* 99(1): 116-135.

[16] Čihák, M., A. Demirgüč-Kunt, E., Feyen and R. Levine. 2013. "Financial Development in 205 Economies, 1960 to 2010." NBER Working Paper 18946. Cambridge, United States: National Bureau of Economic Research.

[17] Clark, T. E. and K. D. West. 2006. "Using Out-of-Sample Mean Squared Prediction Errors to Test the Martingale Difference Hypothesis." *Journal of Econometrics* 135: 155-186.

[18] Clark, T. E. and K. D. West. 2007. "Approximately Normal Tests for Equal Predictive Accuracy in Nested Models." *Journal of Econometrics* 138: 291-311.

[19] Davidson, R. and J. G. MacKinnon. 1989. "Testing for Consistency Using Artificial Regressions." *Econometric Theory* 5: 363-384.

[20] Davidson, R. and J. G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. Oxford, United Kingdom: Oxford University Press.

[21] Diebold, F. X. and R. S. Mariano. 1995. "Comparing Predictive Accuracy." *Journal of Business & Economic Statistics* 13: 253-263.

[22] Friedman, M. and A. J. Schwartz. 1963. *A Monetary History of the United States, 1867-1960*. Princeton, United States: National Bureau of Economic Research and Princeton University Press.

[23] Gaglianone, W.P. and L. R. Lima. 2012. "Constructing Density Forecasts from Quantile Regressions." *Journal of Money, Credit and Banking* 44(8): 1589-1607.

[24] Gauthier, C., C. Graham and Y. Liu. 2004. "Financial Conditions Indexes for Canada." Bank of Canada Working Paper 04-22. Ottawa, Canada: Bank of Canada.

[25] Gertler, M. and S. Gilchrist. 1994. "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms." *The Quarterly Journal of Economics* 109(2): 309-340.

[26] Giacomini, R. and B. Rossi. 2010. "Forecast Comparisons in Unstable Environments." *Journal of Applied Econometrics* 25: 595-620.

[27] Giacomini, R. and H. White. 2006. "Tests of Conditional Predictive Ability." *Econometrica* 74: 1545-1578.

[28] Greene, W. H. 2003. *Econometric Analysis*. Fifth edition. Upper Saddle River, United States: Prentice Hall.

[29] Gumata, N., E. Ndou and N. Klein. 2012. "A Financial Conditions Index for South Africa." IMF Working Papers 12/196. Washington, DC, United States: International Monetary Fund.

[30] Hakkio, C. S. and W. R. Keeton. 2009. "Financial Stress: What is It, How Can It Be Measured, and Why Does It Matter?" *Economic Review* (Second Quarter): 5-50.

[31] Hatzius, J., P. Hooper, F. S. Mishkin, K. L. Schoenholtz and M. W. Watson. 2010. "Financial Conditions Indexes: a Fresh Look after the Financial Crisis." NBER Working Paper 16150. Cambridge, United States: National Bureau of Economic Research.

[32] Hausman, J. A. 1978. "Specification Tests in Econometrics." *Econometrica* 46: 1251-1271.

[33] Hausman, J. A. 2001. "Mismeasured Variables in Econometric Analysis: Problems from the Right and Problems from the Left." *Journal of Economic Perspectives* 15(4): 57-67.

[34] Illing, M. and Y. Liu. 2006. "Measuring Financial Stress in a Developed Country: an Application to Canada." *Journal of Financial Stability* 2(3): 243-265.

[35] International Monetary Fund (IMF). 2012. "Brazil: Financial System Stability Assessment." IMF Country Report 12/206. Washington, DC, United States: IMF. Available at: http://www.imf.org/external/pubs/ft/scr/2012/cr12206.pdf

[36] International Monetary Fund (IMF). 2012b. "Global Financial Stability Report. The Quest for Lasting Stability." Washington, DC, United States: IMF. Available at: http://www.imf.org/external/pubs/ft/gfsr/2012/01/pdf/text.pdf

[37] Johansson, T. and F. Bonthron. 2013. "Further Development of the Index for Financial Stress for Sweden." Sveriges Riksbank Economic Review 2013:1.

[38] Johnson, R. and D. Wichern. 1992. *Applied Multivariate Statistical Analysis*. Upper Saddle River, United States: Prentice-Hall.

[39] Jolliffe, I. T. 2002. *Principal Component Analysis*. Second edition. New York, United States: Springer.

[40] Kara, H., P. Özlü and D. Ünalmış. 2012. "Financial Conditions Indices for the Turkish Economy." CBT Research Notes in Economics 2012-31. Ankara, Turkey: Central Bank of the Republic of Turkey.

[41] Kashyap, A. K., O. A. Lamont and J. C. Stein. 1994. "Credit Conditions and the Cyclical Behavior of Inventories." *The Quarterly Journal of Economics* 109(3): 565-592.

[42] Khwaja, A.I. and A. Mian. 2008. "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market." *American Economic Review* 98(4): 1413-1442.

[43] Kliesen, K.L., M. T. Owyang and E. K. Vermann. 2012. "Disentangling Diverse Measures: A Survey of Financial Stress Indexes." *Federal Reserve Bank of St. Louis Review* 94(5): 369-97..

[44] Koenker, R., 2005. *Quantile Regression*. Cambridge, United Kingdom: Cambridge University Press.

[45] Marcellino, M., J. Stock and M. Watson. 2006. "A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series." *Journal of Econometrics* 135: 499-526.

[46] Murphy, K.M. and R. H. Topel. 1985. "Estimation and Inference in Two-Step Econometric Models." *Journal of Business & Economic Statistics* 3(4): 370-379.

[47] Nelson, W.R. and R. Perli. 2007. "Selected Indicators of Financial Stability." In: *Risk Measurement and Systemic Risk.* Frankfurt, Germany: European Central Bank.

[48] Newey, W.K. and K.D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55: 703-708.

[49] Oliner, S.D. and G. D. Rudebusch. 1996. "Monetary Policy and Credit Conditions: Evidence from the Composition of External Finance: Comment," *American Economic Review* 86(1): 300-309.

[50] Pagan, A. 1984. "Econometric Issues in the Analysis of Regressions With Generated Regressors." *International Economic Review* 25(1): 221-247.

[51] Palm, F.C. and A. Zellner. 1992. "To Combine or Not to Combine? Issues of Combining Forecasts." *Journal of Forecasting* 11(8): 687-701.

[52] Paravisini, D. 2008. "Local Bank Financial Constraints and Firm Access to External Finance." *Journal of Finance* 63(5): 2161-2193.

[53] Peek, J. and E. S. Rosengren. 1997. "The International Transmission of Financial Shocks: The Case of Japan." *American Economic Review* 87(4): 495-505.

[54] Peek, J. and E. S. Rosengren. 2000. "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States." *American Economic Review* 90(1): 30-45.

[55] Pereira da Silva, L.A., A. S. Sales and W. P. Gaglianone. 2012. "Financial Stability in Brazil." Working Paper 289. Brasília, Brazil: Banco Central do Brasil. Available at: http://www.bcb.gov.br/pec/wps/ingl/wps289.pdf

[56] Sales, A. S., W. D. Areosa and M. B. M. Areosa. 2012. "Some Financial Stability Indicators for Brazil." Working Paper 287. Brasília, Brazil: Banco Central do Brasil. Available at: http://www.bcb.gov.br/pec/wps/ingl/wps287.pdf

[57] Sandahl, J.F., M. Holmfeldt, A. Rydén and M. Strömqvist. 2011. "An Index for Financial Stress for Sweden." *Sveriges Riksbank Economic Review* 2011:2.

[58] Stein, J. C. and A. K. Kashyap. 2000. "What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?" *American Economic Review* 90(3): 407-428.

[59] Stock, J. H. and M. W. Watson. 2002. "Forecasting Using Principal Components From a Large Number of Predictors." *Journal of the American Statistical Association* 97: 1167-1179.

[60] Timmermann, A. 2006. "Forecast Combinations." In: G. Elliott, C.W.J. Granger, and A. Timmermann, editors. *Handbook of Economic Forecasting*. Amsterdam, The Netherlands: North-Holland.

Appendix A - Raw Data

Figure A1 - Inflation (IPCA) and Nominal Interest Rates (% p.a.)

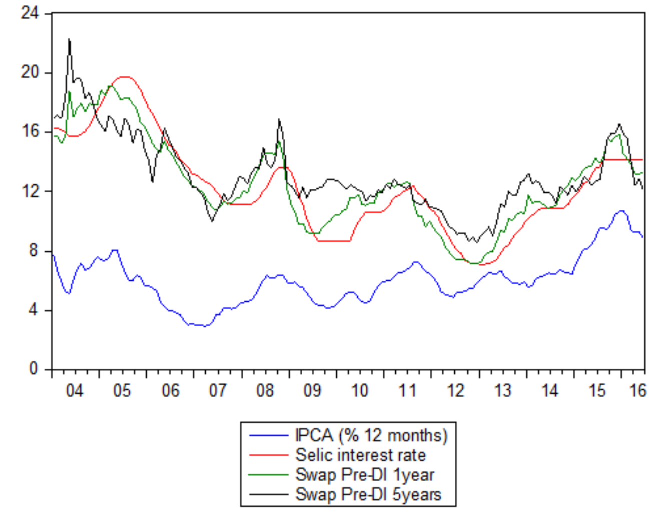


Figure A2 - CDS spread, Embi+Br and VIX

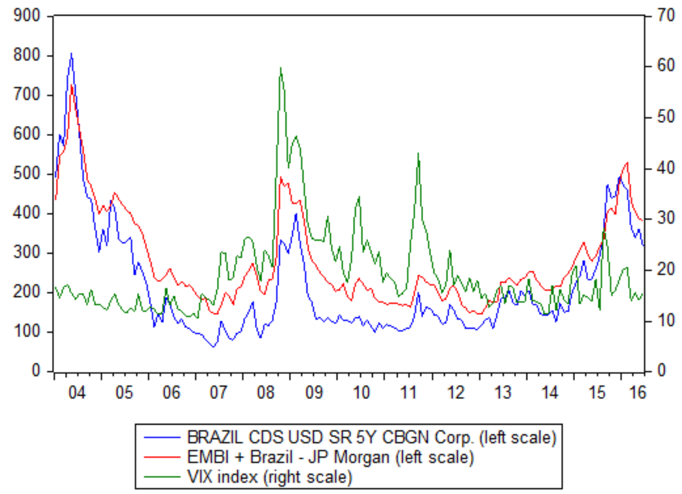


Figure A3 - Nominal Monetary Aggregates
(R$ thousand)

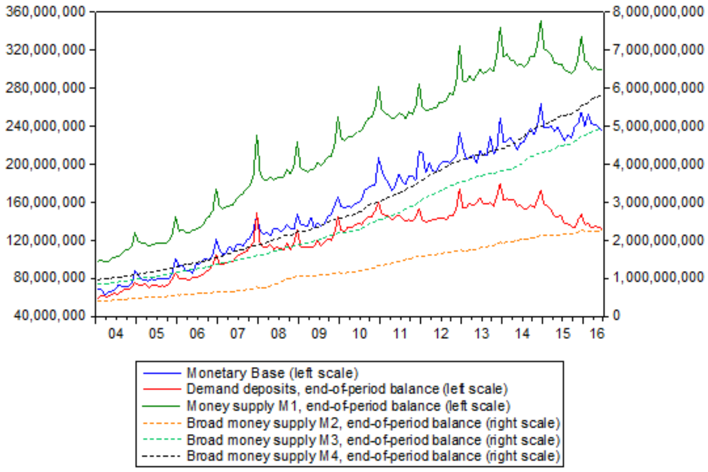


Figure A4 - Nominal Credit Operations Outstanding
(R$ million, nonearmarked operations)

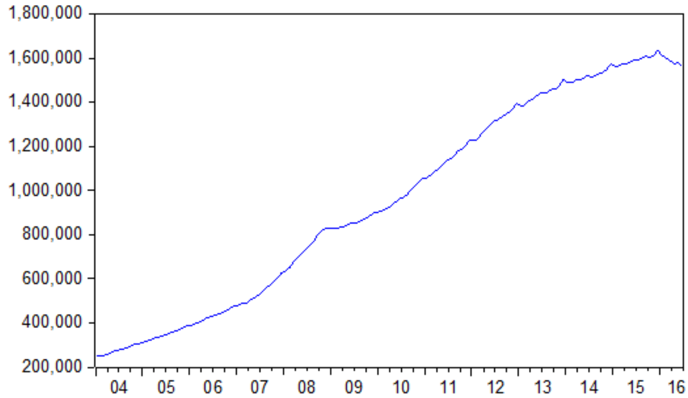


Figure A5 - Banking Credit Indicators

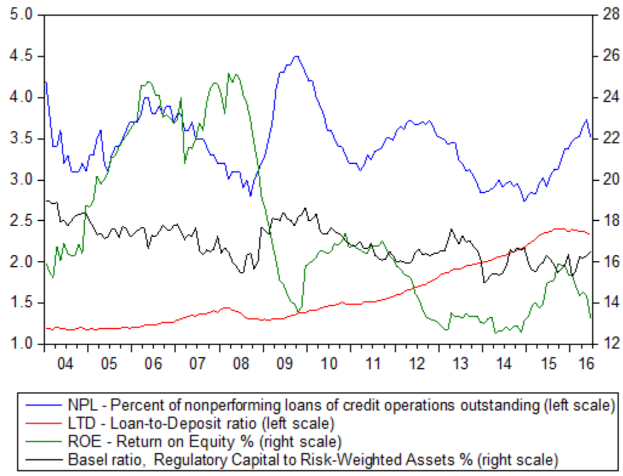


Figure A6 - Capital Markets

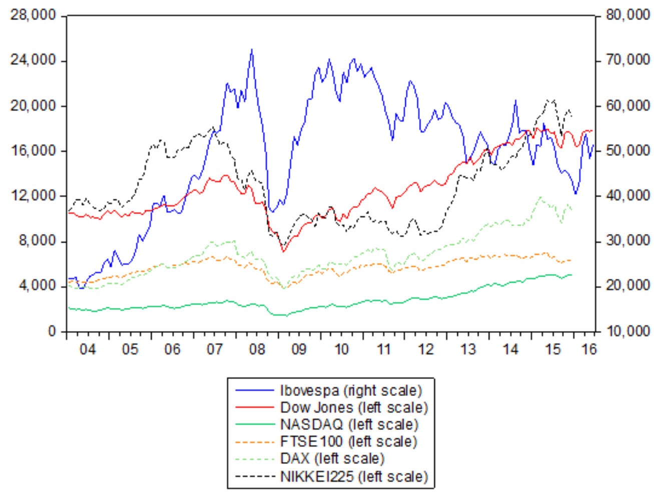
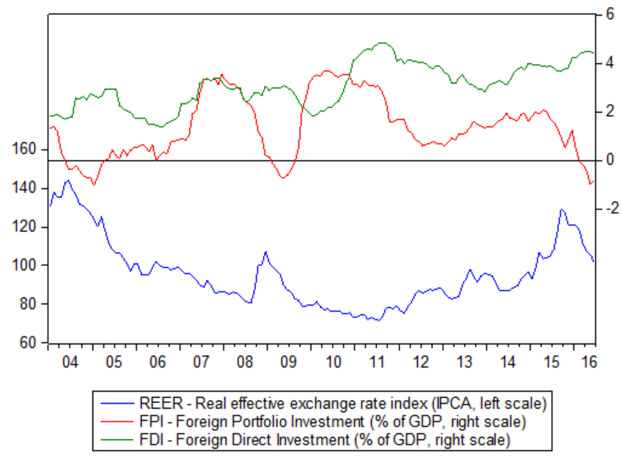


Figure A7 - Real Effective Exchange Rate and Capital Flows (FDI and FPI)



Appendix B - Alternative Regressions

Table B1 - Regression Estimates (IBC-BR)

Dependent Variable: IBC-BR (t)

Regressors	h=1	h=2	h=3	h=6	h=9	h=12
Constant	0.197	0.191	0.162	0.146	0.144	0.149
	(0.01)	(0.013)	(0.073)	(0.176)	(0.16)	(0.17)
AR(1)	0.831	0.827	0.846	0.864	0.863	0.871
	(0)	(0)	(0)	(0)	(0)	(0)
FCI* (t-h)	0.417	0.364	0.132	-0.022	0.150	0.073
	(0.005)	(0.004)	(0.438)	(0.881)	(0.315)	(0.679)
R-squared	0.762	0.757	0.748	0.740	0.745	0.744
Adjusted R-squared	0.759	0.754	0.744	0.736	0.741	0.740
Residual autocorrelation LM test (p-value)						
1lag	0.000	0.000	0.000	0.000	0.000	0.000
4 lags	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test1(p-value)	0.405	0.435	0.440	0.826	0.927	0.385
Hausman test2 (p-value)	0.473	0.538	0.411	0.940	0.251	0.823

Notes: Sample May2004-Jun2016. P-values in parentheses.

Newey and West (1987)'s HAC covariance matrix of residuals.

The null hypothesis of the Hausman test assumes no endogeneity regarding FCI*.

The Hausman test1 employs the vector of instruments $z_t^1 = [\Delta \ln(Embi_{t-h-i})]'$,

whereas the test2 is based on $z_t^2 = [\Delta \ln(CDS_{t-h-i})]'$; for $i = \{0;1;2\}$.

Table B2 - Regression Estimates (Industrial Production)

Dependent Variable: Ind.Production (t)

Regressors	h=1	h=2	h=3	h=6	h=9	h=12
Constant	0.063	0.058	0.008	-0.031	-0.037	-0.027
	(0.542)	(0.574)	(0.951)	(0.855)	(0.825)	(0.875)
AR(1)	0.773	0.766	0.806	0.845	0.843	0.845
	(0)	(0)	(0)	(0)	(0)	(0)
FCI* (t-h)	0.929	0.904	0.363	-0.026	0.131	-0.017
	(0)	(0)	(0.322)	(0.919)	(0.643)	(0.955)
R-squared	0.754	0.750	0.726	0.713	0.713	0.711
Adjusted R-squared	0.750	0.746	0.722	0.709	0.708	0.707
Residual autocorrelation LM test (p-value)						
1lag	0.000	0.000	0.000	0.001	0.001	0.001
4 lags	0.000	0.000	0.000	0.000	0.000	0.000
Hausman test1(p-value)	0.443	0.657	0.392	0.614	0.478	0.819
Hausman test2 (p-value)	0.518	0.811	0.331	0.894	0.826	0.715

Notes: Sample May2004-Jun2016. P-values in parentheses.

Newey and West (1987)'s HAC covariance matrix of residuals.

The null hypothesis of the Hausman test assumes no endogeneity regarding FCI*.

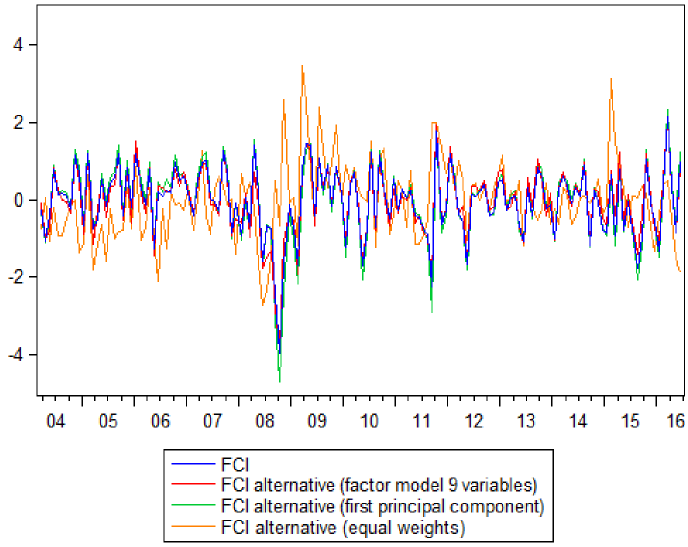
The Hausman test1 employs the vector of instruments $z_t^1 = [\Delta \ln(Embi_{t-h-i})]'$,

whereas the test2 is based on $z_t^2 = [\Delta \ln(CDS_{t-h-i})]'$; for $i = \{0;1;2\}$.

Appendix C - Alternative FCIs

Figure C1 - FCI and Alternative Indicators

(a) Monthly FCIs



(b) FCIs Accumulated in 12 Months

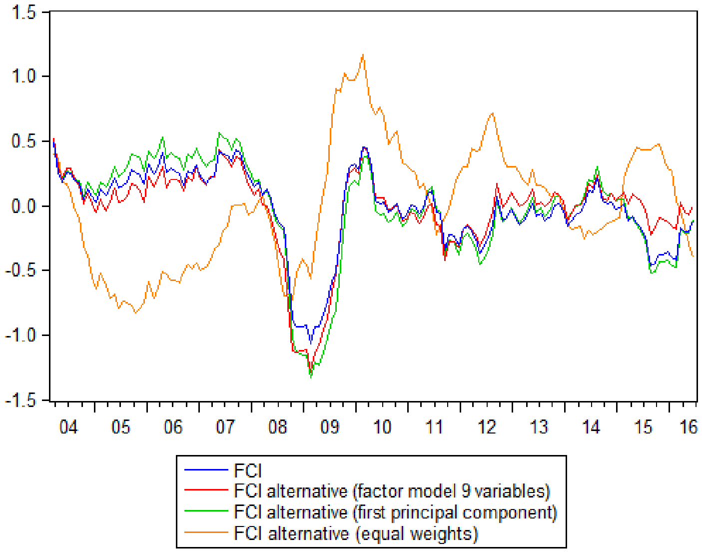


Table C1 - Out-of-Sample Forecast Evaluation (MSFE)

Panel A: IBC-BR (Expanding Sample, FCI^{EW})

h	*M4 lag0*	*M4 lag1*	*M4 lag2*	*M4 lag3*	*M4 lag4*	*M4 lag5*	*M4 lag6*	*M4 lag7*	*M4 lag8*	*M4 lag9*	*M4 lag10*	*M4 lag11*	*M4 lag12*
1	0.039	0.040	0.040	0.040	0.040	0.039	0.038	0.038	0.037	**0.037**	0.037	0.037	0.037
	(0.933)	(0.928)	(0.583)	(0.241)	(0.027)	(0.075)	(0.326)	(0.011)	(0.018)	(0.013)	(0.02)	(0.02)	(0.023)
2	0.042	0.044	0.044	0.042	0.040	0.038	0.037	0.036	**0.035**	0.035	0.035	0.035	0.036
	(0.681)	(0.942)	(0.608)	(0.041)	(0.072)	(0.572)	(0.033)	(0.019)	(0.028)	(0.025)	(0.025)	(0.023)	(0.028)
3	0.046	0.048	0.047	0.044	0.040	0.036	0.033	0.031	**0.031**	0.032	0.032	0.033	0.034
	(0.396)	(0.594)	(0.369)	(0.029)	(0.027)	(0.234)	(0.262)	(0.136)	(0.118)	(0.09)	(0.073)	(0.068)	(0.067)
4	0.086	0.087	0.085	0.080	0.073	0.066	0.062	0.060	**0.059**	0.060	0.060	0.062	0.063
	(0.65)	(0.884)	(0.424)	(0.073)	(0.074)	(0.812)	(0.117)	(0.063)	(0.051)	(0.048)	(0.045)	(0.042)	(0.04)
5	0.102	0.103	0.100	0.093	0.082	0.074	0.068	0.066	**0.065**	0.066	0.067	0.070	0.072
	(0.636)	(0.966)	(0.25)	(0.016)	(0.045)	(0.592)	(0.282)	(0.112)	(0.074)	(0.06)	(0.05)	(0.043)	(0.037)
6	0.130	0.129	0.125	0.113	0.101	0.090	0.083	0.080	**0.078**	0.080	0.083	0.087	0.091
	(0.587)	(0.817)	(0.191)	(0.008)	(0.038)	(0.465)	(0.501)	(0.195)	(0.102)	(0.078)	(0.06)	(0.047)	(0.046)
7	0.170	0.168	0.159	0.146	0.131	0.119	0.110	0.104	**0.103**	0.106	0.110	0.116	0.122
	(0.581)	(0.828)	(0.48)	(0.004)	(0.063)	(0.668)	(0.345)	(0.1)	(0.054)	(0.045)	(0.034)	(0.036)	(0.034)
8	0.187	0.182	0.172	0.158	0.144	0.130	0.121	**0.117**	0.118	0.123	0.130	0.137	0.143
	(0.558)	(0.732)	(0.022)	(0.005)	(0.079)	(0.623)	(0.401)	(0.156)	(0.093)	(0.072)	(0.069)	(0.064)	(0.051)
9	0.211	0.206	0.196	0.183	0.166	0.153	0.147	**0.146**	0.150	0.158	0.164	0.171	0.176
	(0.487)	(0.798)	(0.002)	(0.034)	(0.219)	(0.958)	(0.342)	(0.197)	(0.127)	(0.142)	(0.126)	(0.099)	(0.057)
10	0.240	0.234	0.225	0.211	0.195	0.185	**0.182**	0.182	0.186	0.193	0.199	0.205	0.211
	(0.347)	(0.553)	(0)	(0.033)	(0.23)	(0.896)	(0.579)	(0.327)	(0.265)	(0.24)	(0.181)	(0.114)	(0.091)
11	0.255	0.250	0.240	0.227	0.217	0.212	**0.209**	0.210	0.212	0.217	0.222	0.229	0.235
	(0.244)	(0.344)	(0.016)	(0.143)	(0.35)	(0.779)	(0.657)	(0.511)	(0.333)	(0.245)	(0.162)	(0.144)	(0.116)
12	0.276	0.270	0.262	0.255	0.251	0.246	0.245	0.243	**0.243**	0.246	0.254	0.261	0.268
	(0.195)	(0.186)	(0.916)	(0.461)	(0.489)	(0.979)	(0.791)	(0.601)	(0.323)	(0.229)	(0.232)	(0.255)	(0.252)

Panel B: IBC-BR (Expanding Sample, FCI^{PC1})

h	*M5 lag0*	*M5 lag1*	*M5 lag2*	*M5 lag3*	*M5 lag4*	*M5 lag5*	*M5 lag6*	*M5 lag7*	*M5 lag8*	*M5 lag9*	*M5 lag10*	*M5 lag11*	*M5 lag12*
1	0.039	0.039	0.038	0.038	**0.037**	0.038	0.038	0.038	0.038	0.039	0.039	0.039	0.040
	(0.625)	(0.677)	(0.698)	(0.925)	(0.415)	(0.327)	(0.432)	(0.205)	(0.066)	(0.005)	(0.001)	(0)	(0)
2	0.044	0.042	0.039	0.037	**0.037**	0.037	0.038	0.038	0.039	0.040	0.040	0.041	0.041
	(0.423)	(0.238)	(0.281)	(0.669)	(0.258)	(0.036)	(0.05)	(0.045)	(0.021)	(0.008)	(0.002)	(0.001)	(0)
3	0.050	0.046	0.038	0.034	**0.033**	0.033	0.034	0.035	0.037	0.039	0.041	0.042	0.043
	(0.121)	(0.057)	(0.065)	(0.048)	(0.385)	(0.384)	(0.295)	(0.213)	(0.094)	(0.025)	(0.003)	(0)	(0)
4	0.090	0.081	0.070	0.066	**0.063**	0.064	0.066	0.068	0.072	0.075	0.078	0.080	0.082
	(0.282)	(0.211)	(0.269)	(0.273)	(0.105)	(0.095)	(0.103)	(0.067)	(0.016)	(0.002)	(0)	(0)	(0)
5	0.104	0.091	0.079	0.071	**0.068**	0.070	0.073	0.077	0.082	0.086	0.091	0.095	0.096
	(0.13)	(0.088)	(0.105)	(0.087)	(0.573)	(0.557)	(0.388)	(0.217)	(0.065)	(0.011)	(0.001)	(0)	(0)
6	0.133	0.119	0.098	0.088	**0.082**	0.084	0.089	0.094	0.100	0.106	0.113	0.117	0.119
	(0.104)	(0.073)	(0.086)	(0.101)	(0.869)	(0.973)	(0.666)	(0.413)	(0.126)	(0.018)	(0.001)	(0)	(0)
7	0.178	0.157	0.135	0.118	**0.111**	0.115	0.120	0.127	0.135	0.142	0.149	0.154	0.159
	(0.153)	(0.12)	(0.133)	(0.169)	(0.738)	(0.953)	(0.62)	(0.301)	(0.045)	(0.002)	(0)	(0)	(0)
8	0.190	0.171	0.142	0.125	**0.119**	0.124	0.134	0.141	0.150	0.159	0.167	0.174	0.177
	(0.076)	(0.055)	(0.082)	(0.57)	(0.406)	(0.664)	(0.953)	(0.526)	(0.106)	(0.008)	(0)	(0)	(0)
9	0.219	0.195	0.167	0.152	**0.145**	0.154	0.163	0.171	0.183	0.191	0.200	0.206	0.212
	(0.125)	(0.102)	(0.122)	(0.789)	(0.459)	(0.724)	(0.878)	(0.447)	(0.073)	(0.006)	(0.001)	(0)	(0.001)
10	0.255	0.229	0.200	0.181	**0.179**	0.186	0.194	0.205	0.215	0.223	0.232	0.241	0.246
	(0.121)	(0.089)	(0.12)	(0.301)	(0.191)	(0.375)	(0.766)	(0.61)	(0.118)	(0.014)	(0.004)	(0.004)	(0.003)
11	0.270	0.249	0.220	0.208	**0.205**	0.209	0.220	0.228	0.237	0.246	0.254	0.261	0.268
	(0.142)	(0.102)	(0.111)	(0.274)	(0.209)	(0.417)	(0.936)	(0.536)	(0.12)	(0.031)	(0.021)	(0.023)	(0.02)
12	0.298	0.277	0.260	0.247	**0.240**	0.246	0.252	0.257	0.266	0.272	0.279	0.286	0.294
	(0.288)	(0.22)	(0.243)	(0.415)	(0.24)	(0.611)	(0.932)	(0.354)	(0.072)	(0.027)	(0.018)	(0.02)	(0.093)

Panel C: IBC-BR (Expanding Sample, FCI*)

h	*M6 lag0*	*M6 lag1*	*M6 lag2*	*M6 lag3*	*M6 lag4*	*M6 lag5*	*M6 lag6*	*M6 lag7*	*M6 lag8*	*M6 lag9*	*M6 lag10*	*M6 lag11*	*M6 lag12*
1	0.044	0.045	0.045	0.042	0.038	**0.037**	0.038	0.038	0.038	0.038	0.038	0.038	0.039
	(0)	(0)	(0)	(0.001)	(0.164)	(0.861)	(0.318)	(0.006)	(0.025)	(0.013)	(0.005)	(0.004)	(0.002)
2	0.054	0.054	0.050	0.040	**0.035**	0.036	0.036	0.036	0.036	0.037	0.038	0.039	0.039
	(0)	(0)	(0)	(0.028)	(0.024)	(0.014)	(0.023)	(0.026)	(0.026)	(0.013)	(0.006)	(0.003)	(0.003)
3	0.069	0.070	0.051	0.036	0.030	**0.030**	0.030	0.030	0.031	0.033	0.035	0.038	0.040
	(0)	(0)	(0)	(0.175)	(0.09)	(0.07)	(0.051)	(0.046)	(0.032)	(0.019)	(0.01)	(0.005)	(0.003)
4	0.123	0.113	0.089	0.070	0.058	**0.058**	0.058	0.058	0.061	0.063	0.067	0.071	0.075
	(0)	(0)	(0)	(0.198)	(0.05)	(0.03)	(0.026)	(0.022)	(0.013)	(0.008)	(0.004)	(0.001)	(0)
5	0.140	0.125	0.099	0.071	0.059	**0.058**	0.059	0.061	0.065	0.069	0.076	0.082	0.088
	(0)	(0)	(0)	(0.455)	(0.038)	(0.033)	(0.027)	(0.02)	(0.016)	(0.012)	(0.007)	(0.004)	(0.001)
6	0.175	0.160	0.120	0.086	0.065	**0.064**	0.067	0.070	0.076	0.083	0.093	0.102	0.109
	(0)	(0)	(0.001)	(0.335)	(0.05)	(0.039)	(0.029)	(0.024)	(0.019)	(0.015)	(0.009)	(0.003)	(0.001)
7	0.227	0.203	0.161	0.112	**0.087**	0.087	0.090	0.095	0.104	0.113	0.126	0.136	0.146
	(0)	(0)	(0.008)	(0.206)	(0.039)	(0.023)	(0.019)	(0.017)	(0.015)	(0.012)	(0.006)	(0.003)	(0.001)
8	0.235	0.211	0.152	0.107	**0.086**	0.087	0.095	0.103	0.114	0.127	0.141	0.154	0.164
	(0)	(0)	(0.892)	(0.1)	(0.038)	(0.033)	(0.031)	(0.028)	(0.024)	(0.017)	(0.011)	(0.004)	(0)
9	0.259	0.222	0.168	0.126	**0.103**	0.109	0.119	0.128	0.145	0.158	0.172	0.186	0.197
	(0)	(0.013)	(0.481)	(0.07)	(0.032)	(0.033)	(0.035)	(0.033)	(0.028)	(0.024)	(0.014)	(0.004)	(0)
10	0.288	0.253	0.199	0.147	**0.127**	0.134	0.145	0.160	0.175	0.188	0.205	0.219	0.230
	(0)	(0.203)	(0.481)	(0.018)	(0.076)	(0.061)	(0.051)	(0.042)	(0.033)	(0.023)	(0.009)	(0.002)	(0)
11	0.292	0.260	0.204	0.165	**0.148**	0.154	0.171	0.184	0.199	0.215	0.228	0.240	0.250
	(0.024)	(0.971)	(0.231)	(0.086)	(0.059)	(0.047)	(0.038)	(0.034)	(0.026)	(0.016)	(0.006)	(0.001)	(0)
12	0.309	0.277	0.238	0.205	**0.186**	0.197	0.209	0.218	0.234	0.245	0.257	0.265	0.275
	(0.491)	(0.538)	(0.225)	(0.13)	(0.102)	(0.084)	(0.076)	(0.065)	(0.049)	(0.033)	(0.014)	(0.004)	(0)

Note: The minimum MSFE for each horizon (h) is marked in bold. The p-value of the equal predictive accuracy test of Diebold and Mariano (1995) for non-nested models is shown in parentheses. The MSFE loss is used and model M3 (with its respective lag) is the benchmark. Green cells indicate a rejection of the null (p-value<0.05) and also that MSFE(Mk_lag_i) < MSFE(M3_lag_i) for each i=0,...,12 and k=4,5,6 in Panels A, B and C, respectively.

Table C1 (cont.) - Out-of-Sample Forecast Evaluation (MSFE)

Panel D: IBC-BR (Rolling Window, FCI^{EW})

h	*M4 lag0*	*M4 lag1*	*M4 lag2*	*M4 lag3*	*M4 lag4*	*M4 lag5*	*M4 lag6*	*M4 lag7*	*M4 lag8*	*M4 lag9*	*M4 lag10*	*M4 lag11*	*M4 lag12*
1	**0.039**	0.040	0.042	0.045	0.046	0.050	0.057	0.063	0.067	0.065	0.063	0.059	0.055
	(0.88)	(0.891)	(0.372)	(0.124)	(0.536)	(0.288)	(0.059)	(0.055)	(0.014)	(0.013)	(0.014)	(0.009)	(0.013)
2	**0.039**	0.041	0.045	0.046	0.050	0.057	0.061	0.070	0.068	0.066	0.062	0.057	0.053
	(0.376)	(0.794)	(0.263)	(0.273)	(0.481)	(0.151)	(0.099)	(0.042)	(0.024)	(0.024)	(0.018)	(0.017)	(0.017)
3	**0.035**	0.039	0.040	0.041	0.043	0.042	0.046	0.048	0.048	0.046	0.044	0.044	0.043
	(0.121)	(0.587)	(0.24)	(0.196)	(0.228)	(0.19)	(0.054)	(0.019)	(0.017)	(0.03)	(0.073)	(0.102)	(0.164)
4	**0.070**	0.075	0.083	0.093	0.098	0.100	0.104	0.110	0.105	0.098	0.091	0.086	0.083
	(0.473)	(0.981)	(0.22)	(0.173)	(0.225)	(0.193)	(0.129)	(0.076)	(0.057)	(0.05)	(0.051)	(0.077)	(0.171)
5	**0.078**	0.086	0.096	0.098	0.101	0.095	0.093	0.093	0.088	0.085	0.083	0.083	0.083
	(0.437)	(0.661)	(0.124)	(0.084)	(0.112)	(0.103)	(0.072)	(0.05)	(0.064)	(0.123)	(0.228)	(0.398)	(0.562)
6	0.095	0.106	0.113	0.117	0.116	0.106	0.099	0.095	0.093	**0.093**	0.094	0.096	0.099
	(0.574)	(0.617)	(0.076)	(0.07)	(0.09)	(0.087)	(0.071)	(0.081)	(0.155)	(0.274)	(0.419)	(0.592)	(0.719)
7	0.123	0.135	0.148	0.154	0.156	0.138	0.122	0.113	**0.112**	0.114	0.116	0.120	0.125
	(0.725)	(0.373)	(0.084)	(0.073)	(0.09)	(0.097)	(0.11)	(0.177)	(0.331)	(0.49)	(0.699)	(0.878)	(0.992)
8	0.139	0.153	0.165	0.170	0.168	0.146	0.127	**0.120**	0.123	0.128	0.134	0.139	0.143
	(0.97)	(0.213)	(0.057)	(0.065)	(0.081)	(0.089)	(0.131)	(0.258)	(0.401)	(0.543)	(0.671)	(0.85)	(0.993)
9	0.165	0.179	0.193	0.199	0.195	0.170	0.154	**0.150**	0.154	0.159	0.164	0.166	0.168
	(0.827)	(0.157)	(0.076)	(0.09)	(0.113)	(0.128)	(0.167)	(0.231)	(0.384)	(0.51)	(0.708)	(0.947)	(0.769)
10	0.184	0.198	0.210	0.212	0.205	0.185	0.175	**0.170**	0.173	0.178	0.182	0.185	0.190
	(0.559)	(0.124)	(0.063)	(0.066)	(0.077)	(0.087)	(0.118)	(0.248)	(0.427)	(0.596)	(0.83)	(0.874)	(0.675)
11	0.208	0.222	0.234	0.240	0.241	0.226	0.206	0.196	**0.195**	0.198	0.202	0.208	0.215
	(0.34)	(0.128)	(0.09)	(0.087)	(0.089)	(0.082)	(0.116)	(0.258)	(0.515)	(0.771)	(0.988)	(0.789)	(0.623)
12	0.227	0.242	0.256	0.266	0.272	0.250	0.231	0.219	**0.215**	0.217	0.225	0.233	0.241
	(0.234)	(0.112)	(0.09)	(0.087)	(0.091)	(0.088)	(0.121)	(0.276)	(0.615)	(0.822)	(0.972)	(0.885)	(0.74)

Panel E: IBC-BR (Rolling Window, FCI^{PC1})

h	*M5 lag0*	*M5 lag1*	*M5 lag2*	*M5 lag3*	*M5 lag4*	*M5 lag5*	*M5 lag6*	*M5 lag7*	*M5 lag8*	*M5 lag9*	*M5 lag10*	*M5 lag11*	*M5 lag12*
1	0.040	0.039	0.039	**0.038**	0.044	0.044	0.039	0.046	0.041	0.043	0.045	0.042	0.045
	(0.496)	(0.879)	(0.291)	(0.113)	(0.03)	(0.038)	(0.11)	(0.042)	(0.086)	(0.072)	(0.035)	(0.097)	(0.046)
2	0.044	0.039	**0.036**	0.039	0.045	0.039	0.041	0.042	0.039	0.043	0.041	0.042	0.041
	(0.543)	(0.279)	(0.927)	(0.108)	(0.277)	(0.377)	(0.213)	(0.211)	(0.297)	(0.134)	(0.217)	(0.212)	(0.376)
3	0.044	0.034	0.031	0.032	0.032	0.033	**0.031**	0.032	0.032	0.032	0.034	0.032	0.034
	(0.134)	(0.009)	(0.978)	(0.309)	(0.716)	(0.527)	(0.871)	(0.682)	(0.701)	(0.918)	(0.889)	(0.425)	(0.346)
4	0.078	0.061	0.057	**0.056**	0.062	0.059	0.059	0.062	0.061	0.064	0.063	0.064	0.068
	(0.284)	(0.186)	(0.82)	(0.636)	(0.548)	(0.766)	(0.834)	(0.566)	(0.807)	(0.694)	(0.995)	(0.859)	(0.959)
5	0.083	0.061	**0.052**	0.054	0.055	0.055	0.057	0.058	0.060	0.061	0.064	0.068	0.070
	(0.154)	(0.052)	(0.305)	(0.55)	(0.829)	(0.97)	(0.89)	(0.959)	(0.919)	(0.6)	(0.466)	(0.482)	(0.269)
6	0.090	0.065	0.053	**0.053**	0.054	0.056	0.059	0.062	0.065	0.070	0.075	0.080	0.086
	(0.134)	(0.033)	(0.523)	(0.874)	(0.954)	(0.902)	(0.616)	(0.683)	(0.344)	(0.276)	(0.287)	(0.15)	(0.158)
7	0.109	0.076	**0.064**	0.064	0.067	0.070	0.076	0.080	0.087	0.094	0.101	0.110	0.119
	(0.128)	(0.069)	(0.279)	(0.651)	(0.894)	(0.555)	(0.55)	(0.364)	(0.291)	(0.321)	(0.202)	(0.238)	(0.242)
8	0.103	0.070	**0.057**	0.060	0.062	0.069	0.078	0.085	0.096	0.106	0.116	0.127	0.134
	(0.08)	(0.023)	(0.21)	(0.662)	(0.642)	(0.514)	(0.283)	(0.255)	(0.246)	(0.169)	(0.179)	(0.204)	(0.135)
9	0.116	0.078	**0.066**	0.070	0.073	0.085	0.097	0.106	0.121	0.131	0.144	0.155	0.167
	(0.09)	(0.04)	(0.167)	(0.194)	(0.368)	(0.139)	(0.122)	(0.145)	(0.113)	(0.128)	(0.148)	(0.135)	(0.16)
10	0.121	0.079	**0.065**	0.067	0.076	0.093	0.108	0.124	0.139	0.153	0.166	0.180	0.192
	(0.075)	(0.029)	(0.078)	(0.22)	(0.263)	(0.13)	(0.118)	(0.101)	(0.105)	(0.111)	(0.104)	(0.128)	(0.115)
11	0.126	0.088	**0.071**	0.082	0.093	0.111	0.133	0.147	0.164	0.179	0.192	0.206	0.221
	(0.092)	(0.059)	(0.084)	(0.086)	(0.152)	(0.1)	(0.083)	(0.091)	(0.097)	(0.101)	(0.119)	(0.149)	(0.206)
12	0.139	0.097	**0.094**	0.105	0.116	0.142	0.159	0.172	0.189	0.199	0.212	0.226	0.241
	(0.102)	(0.075)	(0.066)	(0.059)	(0.074)	(0.056)	(0.065)	(0.064)	(0.065)	(0.069)	(0.077)	(0.122)	(0.188)

Panel F: IBC-BR (Rolling Window, FCI*)

h	*M6 lag0*	*M6 lag1*	*M6 lag2*	*M6 lag3*	*M6 lag4*	*M6 lag5*	*M6 lag6*	*M6 lag7*	*M6 lag8*	*M6 lag9*	*M6 lag10*	*M6 lag11*	*M6 lag12*
1	0.042	0.043	0.041	**0.039**	0.040	0.041	0.040	0.041	0.040	0.040	0.040	0.039	0.040
	(0.049)	(0.04)	(0.046)	(0.058)	(0.008)	(0.02)	(0.031)	(0.078)	(0.41)	(0.664)	(0.09)	(0.9)	(0.161)
2	0.050	0.047	0.041	**0.036**	0.039	0.039	0.039	0.039	0.038	0.038	0.038	0.038	0.038
	(0.213)	(0.097)	(0.007)	(0.143)	(0.015)	(0.327)	(0.766)	(0.502)	(0.763)	(0.192)	(0.43)	(0.39)	(0.61)
3	0.055	0.053	0.035	**0.028**	0.030	0.031	0.031	0.031	0.031	0.032	0.032	0.033	0.034
	(0.175)	(0.01)	(0.084)	(0.021)	(0.322)	(0.714)	(0.656)	(0.871)	(0.778)	(0.692)	(0.487)	(0.678)	(0.549)
4	0.101	0.086	0.061	**0.053**	0.055	0.057	0.057	0.057	0.058	0.058	0.059	0.061	0.063
	(0.364)	(0.097)	(0.201)	(0.347)	(0.03)	(0.686)	(0.816)	(0.368)	(0.468)	(0.207)	(0.221)	(0.183)	(0.085)
5	0.112	0.090	0.065	**0.048**	0.052	0.053	0.054	0.055	0.056	0.058	0.061	0.064	0.067
	(0.251)	(0.047)	(0.013)	(0.08)	(0.394)	(0.707)	(0.508)	(0.45)	(0.256)	(0.166)	(0.093)	(0.044)	(0.048)
6	0.126	0.107	0.063	**0.050**	0.051	0.053	0.056	0.058	0.062	0.065	0.070	0.075	0.081
	(0.213)	(0.025)	(0.197)	(0.21)	(0.53)	(0.502)	(0.381)	(0.259)	(0.108)	(0.046)	(0.019)	(0.014)	(0.011)
7	0.154	0.116	0.078	0.060	**0.060**	0.065	0.068	0.072	0.078	0.083	0.091	0.099	0.107
	(0.214)	(0.058)	(0.264)	(0.146)	(0.227)	(0.242)	(0.124)	(0.055)	(0.019)	(0.007)	(0.005)	(0.005)	(0.004)
8	0.149	0.115	0.067	**0.053**	0.056	0.061	0.068	0.073	0.082	0.092	0.101	0.111	0.121
	(0.233)	(0.053)	(0.621)	(0.139)	(0.323)	(0.17)	(0.051)	(0.018)	(0.007)	(0.004)	(0.004)	(0.004)	(0.003)
9	0.164	0.120	0.074	**0.065**	0.065	0.075	0.084	0.090	0.103	0.113	0.125	0.137	0.148
	(0.425)	(0.198)	(0.963)	(0.092)	(0.181)	(0.063)	(0.021)	(0.01)	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)
10	0.169	0.124	0.079	**0.061**	0.063	0.076	0.088	0.102	0.117	0.130	0.145	0.158	0.170
	(0.541)	(0.107)	(0.684)	(0.074)	(0.037)	(0.014)	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)
11	0.173	0.130	0.080	**0.075**	0.075	0.090	0.110	0.123	0.140	0.155	0.168	0.182	0.195
	(0.756)	(0.37)	(0.648)	(0.035)	(0.019)	(0.011)	(0.011)	(0.01)	(0.009)	(0.008)	(0.006)	(0.005)	(0.003)
12	0.183	0.135	0.106	0.097	**0.095**	0.119	0.135	0.149	0.167	0.177	0.190	0.202	0.214
	(0.875)	(0.767)	(0.229)	(0.022)	(0.018)	(0.02)	(0.019)	(0.017)	(0.014)	(0.012)	(0.009)	(0.007)	(0.004)

Note: The minimum MSFE for each horizon (h) is marked in bold. The p-value of the equal predictive accuracy test of Giacomini and White (2006) is shown in parentheses. The MSFE loss is used and model M3 (with its respective lag) is the benchmark. Green cells indicate a rejection of the null (p-value<0.05) and also that MSFE(Mk_lag_i) < MSFE(M3_lag_i) for each i=0,...,12 and k=4,5,6 in Panels D, E and F, respectively.

Table C2 - Out-of-Sample Forecast Evaluation (MSFE)

Panel A: Industrial Production (Expanding Sample, FCI^{EW})

h	*M4 lag0*	*M4 lag1*	*M4 lag2*	*M4 lag3*	*M4 lag4*	*M4 lag5*	*M4 lag6*	*M4 lag7*	*M4 lag8*	*M4 lag9*	*M4 lag10*	*M4 lag11*	*M4 lag12*
1	0.102	0.104	0.105	0.104	0.101	0.099	0.099	0.098	0.098	0.097	0.097	**0.097**	0.097
	(0.208)	(0.155)	(0.026)	(0.018)	(0.338)	(0.463)	(0.008)	(0.003)	(0.073)	(0.054)	(0.066)	(0.063)	(0.071)
2	0.113	0.117	0.117	0.111	0.103	0.099	0.097	0.096	0.096	**0.095**	0.096	0.096	0.096
	(0.818)	(0.314)	(0.063)	(0.122)	(0.91)	(0.075)	(0.027)	(0.11)	(0.17)	(0.161)	(0.149)	(0.142)	(0.171)
3	0.129	0.135	0.130	0.118	0.104	0.094	0.090	**0.089**	0.089	0.090	0.092	0.094	0.095
	(0.624)	(0.847)	(0.112)	(0.052)	(0.094)	(0.592)	(0.334)	(0.308)	(0.284)	(0.223)	(0.194)	(0.203)	(0.236)
4	0.227	0.228	0.218	0.200	0.180	0.165	0.157	0.154	**0.154**	0.155	0.157	0.159	0.161
	(0.863)	(0.428)	(0.074)	(0.1)	(0.587)	(0.102)	(0.086)	(0.118)	(0.12)	(0.111)	(0.113)	(0.118)	(0.13)
5	0.270	0.266	0.251	0.227	0.198	0.179	0.169	0.166	**0.166**	0.167	0.170	0.175	0.179
	(0.946)	(0.346)	(0.04)	(0.03)	(0.212)	(0.434)	(0.191)	(0.153)	(0.129)	(0.118)	(0.111)	(0.109)	(0.103)
6	0.330	0.323	0.304	0.270	0.239	0.216	0.205	0.199	**0.198**	0.201	0.207	0.215	0.221
	(0.978)	(0.431)	(0.013)	(0.01)	(0.146)	(0.637)	(0.221)	(0.147)	(0.121)	(0.11)	(0.1)	(0.087)	(0.084)
7	0.406	0.394	0.368	0.333	0.299	0.275	0.257	0.248	**0.247**	0.253	0.262	0.271	0.279
	(0.959)	(0.324)	(0.011)	(0.014)	(0.282)	(0.497)	(0.12)	(0.075)	(0.066)	(0.065)	(0.054)	(0.053)	(0.045)
8	0.441	0.423	0.396	0.362	0.332	0.302	0.284	**0.278**	0.282	0.293	0.305	0.316	0.322
	(0.889)	(0.343)	(0.001)	(0.011)	(0.207)	(0.666)	(0.175)	(0.108)	(0.091)	(0.079)	(0.07)	(0.058)	(0.04)
9	0.482	0.464	0.439	0.412	0.376	0.345	**0.332**	0.335	0.344	0.355	0.365	0.371	0.373
	(0.969)	(0.271)	(0.001)	(0.055)	(0.512)	(0.391)	(0.141)	(0.124)	(0.103)	(0.102)	(0.077)	(0.051)	(0.025)
10	0.533	0.516	0.498	0.467	0.431	0.406	**0.402**	0.406	0.413	0.424	0.430	0.435	0.441
	(0.657)	(0.549)	(0)	(0.037)	(0.618)	(0.445)	(0.236)	(0.17)	(0.135)	(0.106)	(0.062)	(0.028)	(0.012)
11	0.542	0.530	0.509	0.479	0.459	0.450	**0.448**	0.450	0.451	0.454	0.458	0.466	0.470
	(0.405)	(0.801)	(0.023)	(0.384)	(0.977)	(0.6)	(0.371)	(0.299)	(0.176)	(0.114)	(0.058)	(0.041)	(0.021)
12	0.551	0.537	0.520	0.506	0.501	0.495	0.494	0.490	**0.485**	0.488	0.493	0.501	0.507
	(0.21)	(0.113)	(0.24)	(0.735)	(0.854)	(0.642)	(0.525)	(0.372)	(0.169)	(0.099)	(0.081)	(0.083)	(0.072)

Panel B: Industrial Production (Expanding Sample, FCI^{PC1})

h	*M5 lag0*	*M5 lag1*	*M5 lag2*	*M5 lag3*	*M5 lag4*	*M5 lag5*	*M5 lag6*	*M5 lag7*	*M5 lag8*	*M5 lag9*	*M5 lag10*	*M5 lag11*	*M5 lag12*
1	0.095	**0.095**	0.096	0.096	0.099	0.100	0.101	0.103	0.102	0.103	0.104	0.104	0.105
	(0.213)	(0.457)	(0.175)	(0.04)	(0.038)	(0.024)	(0.024)	(0.001)	(0.001)	(0)	(0)	(0)	(0.001)
2	0.107	0.101	0.098	**0.098**	0.100	0.102	0.104	0.105	0.106	0.109	0.111	0.113	0.111
	(0.534)	(0.498)	(0.955)	(0.696)	(0.021)	(0.017)	(0.013)	(0.01)	(0.007)	(0.003)	(0.001)	(0.001)	(0.001)
3	0.128	0.113	0.096	**0.091**	0.091	0.095	0.099	0.103	0.108	0.114	0.120	0.121	0.119
	(0.044)	(0.018)	(0.045)	(0.034)	(0.139)	(0.074)	(0.042)	(0.017)	(0.006)	(0.002)	(0.001)	(0.001)	(0.001)
4	0.206	0.183	0.166	**0.164**	0.167	0.173	0.180	0.188	0.197	0.206	0.212	0.214	0.212
	(0.332)	(0.289)	(0.501)	(0.009)	(0.005)	(0.002)	(0.001)	(0)	(0)	(0)	(0)	(0)	(0)
5	0.243	0.208	0.184	**0.174**	0.176	0.185	0.196	0.208	0.223	0.233	0.241	0.246	0.244
	(0.078)	(0.059)	(0.087)	(0.013)	(0.07)	(0.03)	(0.01)	(0.003)	(0.001)	(0)	(0)	(0)	(0)
6	0.300	0.260	0.219	0.208	**0.208**	0.220	0.237	0.253	0.269	0.282	0.294	0.300	0.299
	(0.061)	(0.04)	(0.043)	(0.038)	(0.312)	(0.102)	(0.02)	(0.004)	(0.001)	(0)	(0)	(0)	(0)
7	0.375	0.322	0.286	0.269	**0.269**	0.284	0.303	0.321	0.339	0.354	0.367	0.374	0.380
	(0.108)	(0.09)	(0.104)	(0.023)	(0.253)	(0.043)	(0.003)	(0)	(0)	(0)	(0)	(0)	(0)
8	0.404	0.359	0.309	**0.291**	0.293	0.310	0.335	0.354	0.374	0.390	0.404	0.417	0.417
	(0.053)	(0.038)	(0.057)	(0.581)	(0.782)	(0.239)	(0.03)	(0.003)	(0)	(0)	(0)	(0)	(0)
9	0.459	0.408	0.361	**0.347**	0.349	0.370	0.392	0.409	0.431	0.445	0.464	0.471	0.480
	(0.107)	(0.081)	(0.039)	(0.434)	(0.613)	(0.166)	(0.019)	(0.002)	(0)	(0)	(0)	(0.001)	(0.001)
10	0.529	0.478	0.429	**0.407**	0.416	0.434	0.454	0.475	0.494	0.512	0.527	0.543	0.553
	(0.052)	(0.035)	(0.058)	(0.685)	(0.719)	(0.503)	(0.063)	(0.008)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
11	0.553	0.514	0.468	**0.457**	0.461	0.469	0.487	0.499	0.517	0.530	0.546	0.558	0.570
	(0.078)	(0.047)	(0.03)	(0.919)	(0.899)	(0.449)	(0.06)	(0.016)	(0.012)	(0.019)	(0.027)	(0.029)	(0.023)
12	0.582	0.552	0.530	0.512	**0.507**	0.512	0.519	0.526	0.540	0.550	0.562	0.573	0.584
	(0.207)	(0.115)	(0.106)	(0.544)	(0.852)	(0.208)	(0.066)	(0.025)	(0.032)	(0.044)	(0.039)	(0.025)	(0.017)

Panel C: Industrial Production (Expanding Sample, FCI*)

h	*M6 lag0*	*M6 lag1*	*M6 lag2*	*M6 lag3*	*M6 lag4*	*M6 lag5*	*M6 lag6*	*M6 lag7*	*M6 lag8*	*M6 lag9*	*M6 lag10*	*M6 lag11*	*M6 lag12*
1	0.110	0.111	0.104	0.100	**0.098**	0.099	0.099	0.100	0.100	0.100	0.100	0.101	0.101
	(0.001)	(0.001)	(0.017)	(0.071)	(0.249)	(0.02)	(0.051)	(0.05)	(0.078)	(0.046)	(0.021)	(0.016)	(0.01)
2	0.143	0.133	0.116	0.098	**0.096**	0.098	0.099	0.099	0.099	0.101	0.102	0.105	0.106
	(0.003)	(0.003)	(0.026)	(0.849)	(0.059)	(0.101)	(0.083)	(0.074)	(0.06)	(0.04)	(0.024)	(0.014)	(0.01)
3	0.196	0.184	0.123	0.089	**0.083**	0.083	0.085	0.087	0.091	0.096	0.102	0.107	0.111
	(0.002)	(0)	(0)	(0.458)	(0.191)	(0.157)	(0.112)	(0.088)	(0.068)	(0.049)	(0.035)	(0.024)	(0.019)
4	0.312	0.269	0.195	0.161	**0.150**	0.153	0.156	0.159	0.166	0.174	0.184	0.192	0.197
	(0.01)	(0.005)	(0.027)	(0.236)	(0.07)	(0.07)	(0.059)	(0.051)	(0.037)	(0.028)	(0.019)	(0.012)	(0.009)
5	0.362	0.299	0.217	0.162	**0.150**	0.151	0.157	0.165	0.177	0.189	0.204	0.216	0.226
	(0.002)	(0.001)	(0.013)	(0.135)	(0.097)	(0.082)	(0.064)	(0.05)	(0.039)	(0.031)	(0.025)	(0.019)	(0.01)
6	0.430	0.368	0.247	0.188	**0.163**	0.167	0.179	0.190	0.209	0.226	0.246	0.264	0.276
	(0.001)	(0.001)	(0.11)	(0.114)	(0.068)	(0.059)	(0.046)	(0.039)	(0.033)	(0.028)	(0.023)	(0.013)	(0.009)
7	0.517	0.428	0.317	0.235	**0.208**	0.216	0.229	0.246	0.268	0.287	0.313	0.332	0.349
	(0.003)	(0.002)	(0.186)	(0.064)	(0.04)	(0.032)	(0.028)	(0.026)	(0.023)	(0.021)	(0.013)	(0.01)	(0.006)
8	0.528	0.452	0.312	0.235	**0.212**	0.222	0.247	0.268	0.293	0.319	0.346	0.369	0.386
	(0)	(0)	(0.69)	(0.063)	(0.043)	(0.037)	(0.032)	(0.028)	(0.024)	(0.016)	(0.012)	(0.008)	(0.003)
9	0.566	0.473	0.349	0.283	**0.256**	0.276	0.301	0.322	0.353	0.376	0.402	0.425	0.444
	(0.001)	(0.009)	(0.26)	(0.044)	(0.033)	(0.033)	(0.034)	(0.032)	(0.024)	(0.021)	(0.015)	(0.007)	(0.003)
10	0.623	0.539	0.418	0.330	**0.315**	0.335	0.360	0.389	0.416	0.440	0.469	0.493	0.513
	(0)	(0.004)	(0.451)	(0.08)	(0.044)	(0.033)	(0.027)	(0.018)	(0.012)	(0.008)	(0.003)	(0.001)	(0)
11	0.618	0.554	0.439	0.381	**0.369**	0.380	0.406	0.426	0.447	0.471	0.492	0.511	0.529
	(0)	(0.051)	(0.229)	(0.068)	(0.044)	(0.034)	(0.022)	(0.017)	(0.013)	(0.007)	(0.004)	(0.001)	(0)
12	0.623	0.567	0.504	0.454	**0.437**	0.446	0.458	0.467	0.487	0.501	0.517	0.530	0.544
	(0)	(0.846)	(0.208)	(0.102)	(0.075)	(0.048)	(0.038)	(0.028)	(0.018)	(0.012)	(0.005)	(0.002)	(0.001)

Note: The minimum MSFE for each horizon (h) is marked in bold. The p-value of the equal predictive accuracy test of Diebold and Mariano (1995) for non-nested models is shown in parentheses. The MSFE loss is used and model M3 (with its respective lag) is the benchmark. Green cells indicate a rejection of the null (p-value<0.05) and also that MSFE(Mk_lag_i) < MSFE(M3_lag_i) for each i=0,...,12 and k=4,5,6 in Panels A, B and C, respectively.

Table C2 (cont.) - Out-of-Sample Forecast Evaluation (MSFE)

Panel D: Industrial Production (Rolling Window, FCI^{EW})

h	*M4 lag0*	*M4 lag1*	*M4 lag2*	*M4 lag3*	*M4 lag4*	*M4 lag5*	*M4 lag6*	*M4 lag7*	*M4 lag8*	*M4 lag9*	*M4 lag10*	*M4 lag11*	*M4 lag12*
1	**0.106**	0.108	0.114	0.123	0.124	0.134	0.153	0.171	0.180	0.176	0.160	0.148	0.138
	(0.677)	(0.346)	(0.307)	(0.107)	(0.713)	(0.312)	(0.044)	(0.038)	(0.011)	(0.009)	(0.011)	(0.005)	(0.01)
2	**0.109**	0.116	0.129	0.129	0.137	0.153	0.175	0.199	0.197	0.179	0.166	0.153	0.147
	(0.485)	(0.604)	(0.15)	(0.405)	(0.64)	(0.174)	(0.062)	(0.02)	(0.011)	(0.009)	(0.007)	(0.009)	(0.006)
3	**0.106**	0.117	0.117	0.114	0.112	0.120	0.143	0.153	0.146	0.137	0.135	0.137	0.138
	(0.07)	(0.609)	(0.17)	(0.29)	(0.363)	(0.087)	(0.008)	(0.005)	(0.013)	(0.038)	(0.094)	(0.061)	(0.061)
4	**0.192**	0.202	0.216	0.231	0.244	0.262	0.293	0.300	0.285	0.264	0.248	0.236	0.232
	(0.796)	(0.283)	(0.223)	(0.297)	(0.375)	(0.216)	(0.08)	(0.036)	(0.029)	(0.04)	(0.057)	(0.107)	(0.203)
5	**0.216**	0.229	0.242	0.239	0.239	0.238	0.243	0.248	0.240	0.235	0.234	0.237	0.240
	(0.759)	(0.122)	(0.047)	(0.095)	(0.138)	(0.08)	(0.034)	(0.042)	(0.108)	(0.166)	(0.24)	(0.303)	(0.304)
6	**0.248**	0.264	0.271	0.269	0.264	0.250	0.255	0.260	0.262	0.262	0.268	0.275	0.280
	(0.958)	(0.13)	(0.06)	(0.088)	(0.099)	(0.069)	(0.064)	(0.125)	(0.18)	(0.263)	(0.331)	(0.348)	(0.39)
7	**0.301**	0.320	0.336	0.342	0.333	0.308	0.302	0.305	0.305	0.310	0.318	0.326	0.333
	(0.8)	(0.106)	(0.086)	(0.108)	(0.107)	(0.09)	(0.124)	(0.193)	(0.315)	(0.412)	(0.47)	(0.551)	(0.65)
8	0.323	0.344	0.361	0.360	0.350	0.321	**0.318**	0.323	0.334	0.347	0.356	0.361	0.364
	(0.492)	(0.074)	(0.055)	(0.066)	(0.075)	(0.097)	(0.169)	(0.261)	(0.324)	(0.362)	(0.445)	(0.576)	(0.67)
9	**0.359**	0.383	0.399	0.403	0.392	0.367	0.368	0.384	0.396	0.398	0.398	0.398	0.397
	(0.425)	(0.096)	(0.1)	(0.114)	(0.132)	(0.149)	(0.197)	(0.217)	(0.276)	(0.373)	(0.547)	(0.708)	(0.938)
10	**0.384**	0.404	0.419	0.416	0.402	0.391	0.406	0.416	0.415	0.419	0.422	0.422	0.428
	(0.275)	(0.079)	(0.048)	(0.054)	(0.074)	(0.12)	(0.161)	(0.23)	(0.356)	(0.5)	(0.682)	(0.914)	(0.921)
11	**0.398**	0.418	0.432	0.440	0.438	0.435	0.431	0.425	0.424	0.426	0.429	0.438	0.450
	(0.241)	(0.114)	(0.091)	(0.084)	(0.084)	(0.094)	(0.161)	(0.271)	(0.439)	(0.608)	(0.797)	(0.925)	(0.946)
12	**0.408**	0.430	0.451	0.463	0.465	0.448	0.436	0.430	0.426	0.430	0.441	0.456	0.471
	(0.176)	(0.117)	(0.097)	(0.09)	(0.095)	(0.125)	(0.209)	(0.356)	(0.585)	(0.709)	(0.801)	(0.863)	(0.955)

Panel E: Industrial Production (Rolling Window, FCI^{PC1})

h	*M5 lag0*	*M5 lag1*	*M5 lag2*	*M5 lag3*	*M5 lag4*	*M5 lag5*	*M5 lag6*	*M5 lag7*	*M5 lag8*	*M5 lag9*	*M5 lag10*	*M5 lag11*	*M5 lag12*
1	0.101	**0.099**	0.110	0.103	0.122	0.124	0.112	0.131	0.119	0.120	0.132	0.123	0.132
	(0.783)	(0.452)	(0.02)	(0.014)	(0.083)	(0.062)	(0.064)	(0.038)	(0.035)	(0.039)	(0.019)	(0.028)	(0.02)
2	0.115	0.106	**0.104**	0.116	0.129	0.115	0.123	0.122	0.115	0.128	0.123	0.127	0.111
	(0.363)	(0.746)	(0.144)	(0.175)	(0.364)	(0.314)	(0.163)	(0.145)	(0.175)	(0.097)	(0.127)	(0.116)	(0.344)
3	0.119	0.091	0.096	0.099	0.097	0.099	0.093	0.096	0.098	0.097	0.100	**0.089**	0.089
	(0.029)	(0.012)	(0.437)	(0.379)	(0.482)	(0.327)	(0.478)	(0.475)	(0.474)	(0.7)	(0.737)	(0.307)	(0.186)
4	0.174	**0.151**	0.170	0.167	0.184	0.175	0.172	0.184	0.180	0.189	0.174	0.173	0.183
	(0.244)	(0.672)	(0.159)	(0.505)	(0.544)	(0.523)	(0.534)	(0.398)	(0.472)	(0.448)	(0.85)	(0.962)	(0.948)
5	0.184	0.148	**0.145**	0.156	0.157	0.154	0.162	0.163	0.170	0.163	0.166	0.175	0.172
	(0.081)	(0.224)	(0.393)	(0.398)	(0.57)	(0.694)	(0.624)	(0.816)	(0.854)	(0.513)	(0.31)	(0.326)	(0.095)
6	0.191	**0.147**	0.154	0.152	0.154	0.161	0.165	0.174	0.174	0.182	0.194	0.198	0.207
	(0.071)	(0.071)	(0.263)	(0.576)	(0.714)	(0.767)	(0.937)	(0.892)	(0.329)	(0.196)	(0.221)	(0.059)	(0.058)
7	0.216	**0.170**	0.174	0.179	0.186	0.192	0.205	0.209	0.222	0.238	0.248	0.263	0.278
	(0.086)	(0.318)	(0.62)	(0.931)	(0.993)	(0.681)	(0.671)	(0.292)	(0.232)	(0.288)	(0.123)	(0.146)	(0.143)
8	0.202	**0.152**	0.157	0.165	0.170	0.187	0.203	0.219	0.240	0.255	0.274	0.294	0.303
	(0.062)	(0.08)	(0.848)	(0.908)	(0.627)	(0.453)	(0.178)	(0.139)	(0.173)	(0.084)	(0.091)	(0.112)	(0.049)
9	0.215	**0.169**	0.178	0.188	0.197	0.219	0.240	0.259	0.281	0.300	0.323	0.340	0.361
	(0.087)	(0.099)	(0.633)	(0.214)	(0.227)	(0.091)	(0.094)	(0.12)	(0.091)	(0.11)	(0.143)	(0.108)	(0.123)
10	0.221	0.167	**0.166**	0.180	0.206	0.238	0.264	0.292	0.316	0.339	0.361	0.383	0.402
	(0.058)	(0.032)	(0.19)	(0.189)	(0.113)	(0.091)	(0.093)	(0.077)	(0.081)	(0.086)	(0.071)	(0.082)	(0.063)
11	0.223	0.176	**0.173**	0.209	0.236	0.265	0.297	0.317	0.338	0.360	0.379	0.399	0.420
	(0.097)	(0.073)	(0.106)	(0.081)	(0.086)	(0.085)	(0.083)	(0.087)	(0.097)	(0.096)	(0.107)	(0.108)	(0.099)
12	0.233	**0.188**	0.217	0.252	0.275	0.309	0.327	0.343	0.363	0.375	0.391	0.408	0.428
	(0.112)	(0.087)	(0.073)	(0.077)	(0.079)	(0.074)	(0.08)	(0.079)	(0.08)	(0.083)	(0.079)	(0.073)	(0.071)

Panel F: Industrial Production (Rolling Window, FCI*)

h	*M6 lag0*	*M6 lag1*	*M6 lag2*	*M6 lag3*	*M6 lag4*	*M6 lag5*	*M6 lag6*	*M6 lag7*	*M6 lag8*	*M6 lag9*	*M6 lag10*	*M6 lag11*	*M6 lag12*
1	0.113	0.109	**0.103**	0.103	0.112	0.114	0.110	0.113	0.110	0.109	0.109	0.107	0.110
	(0.028)	(0.022)	(0.923)	(0.081)	(0.029)	(0.117)	(0.123)	(0.073)	(0.799)	(0.634)	(0.058)	(0.483)	(0.17)
2	0.138	0.116	**0.101**	0.106	0.114	0.112	0.111	0.110	0.108	0.108	0.107	0.110	0.108
	(0.113)	(0.285)	(0.47)	(0.042)	(0.14)	(0.697)	(0.573)	(0.559)	(0.801)	(0.305)	(0.493)	(0.626)	(0.528)
3	0.156	0.130	0.086	**0.086**	0.090	0.090	0.090	0.091	0.092	0.094	0.097	0.098	0.100
	(0.19)	(0.01)	(0.42)	(0.199)	(0.671)	(0.75)	(0.906)	(0.989)	(0.867)	(0.966)	(0.931)	(0.526)	(0.515)
4	0.244	0.180	**0.139**	0.151	0.162	0.164	0.162	0.161	0.163	0.167	0.168	0.172	0.177
	(0.031)	(0.077)	(0.114)	(0.008)	(0.283)	(0.713)	(0.821)	(0.458)	(0.561)	(0.406)	(0.763)	(0.837)	(0.599)
5	0.262	0.182	**0.134**	0.135	0.146	0.149	0.150	0.155	0.160	0.165	0.171	0.178	0.183
	(0.055)	(0.202)	(0.64)	(0.29)	(0.763)	(0.918)	(0.704)	(0.721)	(0.586)	(0.725)	(0.658)	(0.495)	(0.597)
6	0.275	0.201	**0.129**	0.137	0.145	0.149	0.156	0.164	0.172	0.181	0.191	0.200	0.210
	(0.048)	(0.034)	(0.304)	(0.47)	(0.789)	(0.632)	(0.561)	(0.472)	(0.405)	(0.302)	(0.204)	(0.208)	(0.192)
7	0.317	0.205	**0.152**	0.160	0.168	0.178	0.187	0.197	0.209	0.220	0.235	0.248	0.264
	(0.011)	(0.351)	(0.245)	(0.26)	(0.432)	(0.375)	(0.253)	(0.188)	(0.106)	(0.065)	(0.054)	(0.049)	(0.05)
8	0.294	0.197	**0.133**	0.140	0.152	0.165	0.184	0.198	0.215	0.233	0.251	0.269	0.285
	(0.155)	(0.336)	(0.22)	(0.238)	(0.325)	(0.201)	(0.104)	(0.056)	(0.031)	(0.023)	(0.021)	(0.023)	(0.029)
9	0.306	0.201	**0.150**	0.166	0.174	0.198	0.216	0.230	0.253	0.269	0.289	0.309	0.328
	(0.311)	(0.756)	(0.107)	(0.135)	(0.157)	(0.081)	(0.04)	(0.023)	(0.017)	(0.015)	(0.014)	(0.019)	(0.021)
10	0.311	0.218	0.159	**0.154**	0.173	0.204	0.229	0.256	0.280	0.301	0.326	0.346	0.368
	(0.506)	(0.406)	(0.389)	(0.076)	(0.032)	(0.016)	(0.01)	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
11	0.303	0.226	**0.164**	0.185	0.201	0.228	0.260	0.280	0.301	0.323	0.340	0.359	0.378
	(0.817)	(0.662)	(0.185)	(0.045)	(0.025)	(0.016)	(0.012)	(0.01)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
12	0.302	0.226	**0.212**	0.226	0.240	0.275	0.294	0.310	0.330	0.342	0.357	0.371	0.387
	(0.84)	(0.819)	(0.095)	(0.048)	(0.036)	(0.025)	(0.019)	(0.014)	(0.011)	(0.009)	(0.007)	(0.007)	(0.006)

Note: The minimum MSFE for each horizon (h) is marked in bold. The p-value of the equal predictive accuracy test of Giacomini and White (2006) is shown in parentheses. The MSFE loss is used and model M3 (with its respective lag) is the benchmark. Green cells indicate a rejection of the null (p-value<0.05) and also that MSFE(Mk_lag_i) < MSFE(M3_lag_i) for each i=0,...,12 and k=4,5,6 in Panels D, E and F, respectively.