Forecasting the Brazilian Yield Curve Using Forward-Looking Variables

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Abstract: This paper proposes a forecasting model that combines a factor augmented VAR (FAVAR) methodology with the Nelson and Siegel (NS) parametrization of the yield curve to predict the Brazilian term structure of interest rates. Importantly, we extract the principal components for the FAVAR from a large data set containing forward-looking macroeconomic and financial variables. Our forecasting model significantly improves the predicting accuracy of extant models in the literature, particularly at short-term horizons. For instance, the mean absolute forecast errors are 15-40% lower than the random walk benchmark on predictions at the three month horizon. The out-of-sample analysis shows that including forward-looking indicators is the key to improve the predictive ability of the model.

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1. Introduction

The yield curve of treasury bonds plays a central role in pricing financial assets and in shaping market expectations. As such, accurate forecasts of the yield curve are of great importance for the Treasury, central bankers and market participants in general. Unfortunately, extant models in the literature are not able to consistently outperform the random walk benchmark at short horizons and, at the same time, provide good forecasts at longer horizons.

In this paper, we propose a forecasting strategy for the yield curve that achieves this. We provide out-of-sample evidence that our forecasting model improves on the random walk benchmark at short-horizons (as early as one-month ahead) and, at the same time, provide more accurate forecasts than extant models at longer horizons. The key ingredient of our strategy is to rely on a comprehensive data set of macroeconomic and financial variables that are mostly forward-looking variables. In particular, we proceed in three steps. In the first, we estimate the entire yield curve using the Nelson and Siegel (NS) parametrization of the yield curve. The NS parametrization successfully summarize the variation of yield curve by the level, slope and curvature factors. In the second stage, we predict the future path of these factors using a comprehensive data set of macroeconomic and financial variables by estimating a Factor Augmented VAR (FAVAR) model. Finally, we form forecasts of the yield curve for each maturity at different horizons using the predicted evolution of the level, slope and curvature factors.

To ensure real time forecasts, we redo these three steps at every prediction point. As our forecasting model combines a Nelson-Siegel decomposition of the yield curve with a FAVAR specification, we denote it by NS-FAVAR. Our forecasts of the yield curve beat the random walk benchmark as early as at the one-month horizon. This represents a significant improvement given that the available models produce meaningful predictions only as from the 6-month horizon (see Diebold and Li, 2006; and Moench, 2008). At the one-month horizon, our model forecast errors are 5% lower than those of the random walk benchmark, whereas at longer horizons, our model produce 20% to 40% lower forecast errors than the random walk benchmark.

Important to the superior short-horizon performance of our forecasting strategy is the usage of comprehensive data set that contains a wide array of forward-looking macroeconomic and financial variables. In this respect, Brazilian economic data sets provide a surprisingly rich array of variables. As a consequence of a high-inflationary past, Brazilian market participants consume a variety of price indexes and price expectations indexes, some available at the weekly and even daily frequencies. Moreover, in an effort to increase the transparency of the monetary policy and guide market expectations, a large number of macroeconomic and financial expectations time-series are readily available. Our data set contains 142 macroeconomic and financial variables at the weekly frequency, of which 40% are forward-looking indicators. Examples of macroeconomic forward-looking variables that importantly contribute to our forecasts are the market expectations of GDP growth, of the federal government balance sheet and of the debt-to-GDP ratio.

Our forecasting strategy builds on Diebold et al. (2006). However, instead of including only a few macroeconomic variables, we use a comprehensive data set of 103 macroeconomic variables and 39 financial indicators. To deal with the large number of conditioning variables, we implement Bernanke et al.'s (2005) FAVAR econometric model. The FAVAR model restricts attention to the dynamics of a few principal components that summarize the variation in the data set. We show that conditioning on a broader information set, with many forward-looking macro-financial indicators is key to improve predictability.

This is not the first paper to improve yield curve forecasts at shorter horizons. de Pooter et al. (2010) study models with and without arbitrage restrictions that use macroeconomic information. They find that autoregressive models with macroeconomic predictors entail superior performance at shorter horizons, but fail to improve on the random walk benchmark at longer horizons. Exterkate et al. (2013) discuss the importance of relying on large data sets to improve yield curve forecasts at short horizons. The authors show that factor augmented Nelson and Siegel model are able to improve short-term forecast during volatile periods, but cannot improve on simpler models in periods of low volatility.

In addition, we are also not the first to advocate for the use of forward-looking variables. Altavilla et al. (2014a,b) use market and survey expectations to produce lower short-term forecasting errors of the short-term yields at the 3- and 6-month horizons. However, they are neither able to improve forecasts at longer horizons nor ameliorate longer-term yield predictions. In contrast, van Dijk et al. (2014) improve the forecasting performance for long maturities and at longer horizons by allowing shifting endpoints in the yield curve factors, though their forecasts are weak at shorter horizons.

To sum up, we contribute by ameliorating term structure forecasts for virtually every maturity even at short horizons. We argue that the key is to condition on the information set spanned by a few principal components of a wide array of mainly forward-looking macro-financial indicators.

We organize the remainder of this paper as follows: Section 2 reviews the Nelson-Siegel approach to the modelling of the term structure of interest rates and describes our forecasting strategy. Section 3 describes the data set, whereas Section 4 discusses the out-of-sample results of our forecasting strategy. Section 5 contains several robustness exercises. Section 6 offers some concluding remarks.

2. The forecasting strategy

Our forecasting strategy is in three steps. In the first, we estimate the entire yield curve using the Nelson and Siegel (NS) parametrization of the yield curve. In the second stage, we predict the evolution of the level, slope and curvature factors using a FAVAR approach. Finally, we back out yield forecasts for each maturity at different horizons using the predicted future path of the NS factors.

As such, our forecasting strategy is very similar to Diebold et al.'s (2006) VAR model for the level, slope and curvature factors. The main difference is that they employ only a few macroeconomic variables, whilst we condition on a much broader information set. We do so by following Stock and Watson's (2002b) idea of conditioning on a small number of principal components from a wide array of macroeconomic and financial variables. In particular, we employ a FAVAR model for the level, slope, curvature factors of the yield curve and for the principal components from a data set of 142 macroeconomic and financial variables.

The Nelson-Siegel decomposition of the yield curve posits that we may approximate the yield with maturity *n* by

$$(1) \qquad \hat{y}_t^{(n)} = \hat{\beta}_{1t} + \hat{\beta}_{2t}\left(\frac{1-e^{-\lambda n}}{\lambda n}\right) + \hat{\beta}_{3t}\left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n}\right),$$

where the betas may vary over time, capturing changes in the level, slope and curvature of the term structure, respectively. The NS decomposition allows one to form predictions of the entire yield curve by simply predicting the dynamics of the level, slope and curvature factors. As in Stock and Watson (2002b), we extract the principal components of a comprehensive data set of 142 macroeconomic and financial predictors at the weekly frequency to proxy for the broad economic conditions.[1]

[1] Although the principal component analysis formally requires independent and identically distributed observations, Stock and Watson (2002a) and Doz et al. (2012) show that it performs similarly to full

To write down a FAVAR model. Denote the Nelson-Siegel factors as $Z_t = (\beta_{1t}, \beta_{2t}, \beta_{3t})'$ and the (k×1)-vector F_t of the principal components augmented with the SELIC interest rate (the target interest rate of Brazilian Central Bank). Also, let c denote a (k+3)×1 vector of constants, $\Phi(L)$ a (k+3)×(k+3) first-order autoregressive matrix, and ω_t a vector of reduced form shocks. The FAVAR then reads

(2) $$\begin{pmatrix} F_t \\ Z_t \end{pmatrix} = c + \Phi(L) \begin{pmatrix} F_t \\ Z_t \end{pmatrix} + \omega_t.$$

Bernanke et al. (2005) propose two ways of estimating a FAVAR model: (i) two-step estimation (principal components plus VAR estimation) or (ii) a Bayesian method based on Gibbs sampling. They show that both methods produce similar results, though the two-step estimation not only is computationally simpler, but also yields results that are more plausible. Accordingly, we estimate the FAVAR model using the two-step estimation procedure. We first extract the level, slope and curvature factors of the yield curve as well as the k principal components from our large data set of conditioning variables. We then estimate the coefficients in equation (2) in order to form predictions of the evolution of the NS factors as follows

(3) $$\hat{\beta}_{i,t} = \hat{c}_i + \sum_{j=1}^{3} \hat{\varphi}_{i,k+j} \hat{\beta}_{j,t-1} + \sum_{j=1}^{k} \hat{\varphi}_{i,j} \mathrm{F}_{j,t-1}.$$

Finally, we compute the maximum likelihood forecasts of the yield curve h-month ahead given the future values of the level, slope and curvature factors $(\beta_{1,t+h}, \beta_{2,t+h}, \beta_{3,t+h})$ using only information from up until time t:

(4) $$\hat{y}_{t+h|t}^{(n)} = \hat{\beta}_{1,t+h|t} + \hat{\beta}_{2,t+h|t} \left(\frac{1-e^{-\lambda n}}{\lambda n} \right) + \hat{\beta}_{3,t+h|t} \left(\frac{1-e^{-\lambda n}}{\lambda n} - e^{-\lambda n} \right).$$

More specifically, we consider forecasting horizons of h = 1, 3, 6, 9 and 12 months, which respectively translate into 4, 13, 26, 39 and 52 weeks at our frequency of analysis.

3. Data set

Brazilian economic data sets are relatively comprehensive when it comes to inflation measures and markets expectations. As a consequence of a high-inflationary past, Brazilian market participants consume a variety of price indexes and price expectations indexes, some available at the weekly and even daily frequencies. Moreover, in an effort to increase the transparency of the monetary policy and guide market expectations, a large number of macroeconomic and financial expectations time-series

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maximum likelihood estimation for a large panel in the context of both static and dynamic factor models, respectively.

are readily available. To monitor market expectations, the latter weekly releases the Focus report, with market forecasts of daily indicators of activity, inflation, external and fiscal accounts for current month or year until projections for next 5 years ahead. This set of high frequency indicators has relevant forward-looking information about the Brazilian economy.

Altogether, this means the Brazilian data provide lots of useful high-frequency information about future movements in the yield curve. In particular, we focus on a data set with 142 weekly indicators from the first week of March 2007 to the last week of December 2014. We consider data only as from March 2007 because the Brazilian Treasury starts issuing longer-term bonds by the end of 2006, but liquidity picks up only in 2007. As a robustness check, we run a similar forecasting exercise for a longer sample starting on 2002, but restricting attention to shorter-term interest rates.

We entertain a multitude of data sources. Real activity is the largest group and gather 27% of the database. They are mainly from the Central Bank of Brazil, except to a couple of daily activity indicators (e.g., electric energy consumption and credit variables). All indicators released by the Central bank of Brazil (namely, GDP, GDP services, Industrial production and external accounts) concern market expectations over a certain horizon, e.g. current month, next year, or next 5 years. All expectations data come from the weekly Focus report that the Central Bank of Brazil releases every Monday. Apart from mean and median forecasts, the Focus database also includes information about the standard deviations of the short- and medium-term forecasts of inflation, activity, fiscal and balance payments series. They amount to the second largest group of data, with a share of 23% of the overall database.

Inflation-related variables computed from commodity, producer and consumer price indices constitute 20% of the database. They relate to price changes in the last month as well as expected variation in the current month or in a determined period (e.g. next 12 months or in 5 years). Producer prices are from CEASA, a distribution center for crops, fruits and vegetables, and other cooperatives. We gather commodity prices from Bloomberg, whereas we collect consumer prices at the weekly frequency from FIPE (São Paulo only). The share of fiscal series is 6% of the database. It collects indicators from Focus report as net sovereign debt, primary and nominal budget balance. Altogether, 56% of the inflation, real activity and fiscal time series we consider are forward-looking indicators, thereof providing more timely information about the Brazilian outlook in the short and long term.

Finally, we extract financial and risk indicators from Bloomberg. They correspond to 15% and 9% of the database, respectively. They include real-time indicators of the Brazilian economy, such as the 5-year Brazil CDS, the local stock market index, and the currency contracts outstanding, as well as of the global economy, such as the US financial index, Latin America EMBI and the fed funds rate.

To extract principal components from this broad range of variables, we first make sure that every time series is stationary by taking first differences, if necessary. We construct diffusion indices in two different manners. First, we extract the first two principal components of the full set of indicators in the database, as in Exterkate et al. (2013). Table 1 displays the variables that have the highest correlations with each principal component. The first component explains more than 33% of the overall variation and correlates mostly with Emerging Market Bond Index for Latin America, US yield curve and with the Brazilian external account. The second relates chiefly to uncertainty of forecasting variables and inflation indicators.

As an alternative, we also consider extracting principal components only from forward-looking indicators. Table 2 reveals that the first component explains almost 40% of the forward-looking subset. It correlates mostly with external indicators, as external sector (import growth and trade balance annual change) and asset pricing (bonds and Brazilian Real risk reversal for 3 months[2]). The second principal component, as in the overall database, relates mostly to economy forecasting uncertainty in that it involves mainly the standard deviation of analysts forecasting.

Differently from the US Treasury emissions, the Brazilian Treasury issues bonds with a specific expiration date. For example, in January 2016, the Treasury issued a fixed rate bond with a maturity of 11 years, expiring in January 2027 (NTN-F 27). This feature of the Brazilian term structure of government bonds makes the Nelson-Siegel decomposition particularly interesting for it allows us to back out a fixed maturity yield curve. We estimate weekly level, slope and curvature factors given by the betas in equation (1), but keep λ constant. We fix the value of λ at which the mean absolute difference between the actual and estimated yields is smallest for the training period ranging from 2007 to 2011. This yields a much higher value for λ at 0.195 than Diebold and Li’s (2006) chosen value of 0.0609 to fit the term structure in the US.

4. Empirical analysis

4.1 Preliminary results

[2] Risk reversal is a difference in 25-delta volatility between puts and calls on out-of-money options on the Brazilian currency.

Bernanke and Boivin (2003) show that central bankers benefit from considering a wide range of data to make decisions about interest rates. They conclude this by showing that dimension-reduction techniques, such as Stock and Watson's (2002b) diffusion indices, typically improve the forecast of economy and inflation indicators, with clear benefits to the estimation of the central bank's reaction function. Next, we show that the same applies to Brazilian central bankers.

Table 3 shows the results of regressing the SELIC interest rate on the overall principal components as well as on the forward-looking dataset principal component. The principal components are jointly significant, even if the loading on the second principal component is not statistically different from zero. As expected, the estimates indicate that higher uncertainty about the future and external deterioration leads to higher interest rates.

To assess whether the reaction function of the Central Bank of Brazil responds to a wider array of indicators, we adapt Bernanke and Boivin's (2003) augmented Taylor rule to the weekly frequency as follows:

(5) $$R_t = \rho R_{t-1} + (1-\rho)\left[\beta_1\left(CPI_{12m} - CPI_{5y}\right) + \beta_2\left(g_{12m} - g_{5y}\right) + \beta_3 \widehat{R_t}\right]$$

where $\widehat{R_t} = \hat{c} + \sum_{i=1}^{n} \widehat{a_i} F_{it}$ so as to explicitly link the target SELIC rate R_t to the diffusion indices F_{it} (namely, the two principal components from a set of indicators). We proxy the inflation and growth gaps by the difference between the expected inflation and GDP growth over the next 12 months and the expected inflation and GDP growth in the long run (as measured by market expectations over the next 5 years in the Focus database). Table 4 shows that the information on the principal components is indeed useful for the policymaker decision.

Table 5 shows that the yield curve also responds in a statistically significant manner to the variation in the principal components even controlling for the SELIC rate. The first principal component has a positive effect on the yields, with magnitude seemingly increasing with maturity. This confirms the importance of the external channel transmission on the Brazilian yield curve. The second principal component, which correlates mostly with uncertainty and real activity growth, has a negative effect only on shorter maturities.

Table 6 reports some descriptive statistics for residuals of the NS-FAVAR models. We find that the FAVAR models do a very good job in fitting the level, slope and curvature of the Brazilian yield curve. The mean absolute errors are not only small at about 10 bps, but also very stable across maturities. Our findings corroborate the results in

Moench (2008) and Faria and Almeida (2014) in that mean absolute errors increase with the maturity. The largest error for almost every maturity is in the second half of 2008. The only exception is the 2-year yield, for which the largest error occurs when Brazilian Central Bank has surprised the market by bringing the SELIC rate to its lowest historical value by the end of 2010.

Altogether, we find that the principal components convey important information. In the next section, we examine whether the good in-sample performance also translates into superior forecasts.

4.2 Out-of-sample analysis

In this section, we assess the forecasting performance of our NS-FAVAR model relative to the extant models in the literature. To evaluate the relative importance of the forward-looking variables, we compare the forecasting ability of NS-FAVAR(all), which extracts principal components from the full database, with NS-FAVAR(fwrd) that restricts attention to forward-looking variables only.

We contemplate a number of alternative forecasting model. As usual, we employ a random walk without drift (RW) as a benchmark.[3] Joslin et al. (2011) show that the random walk is actually a very challenging benchmark at shorter forecasting horizons. In addition, we also consider a simple autoregressive model (AR), Diebold and Li's (2006) AR model for the level, slope and curvature factors (DL-AR), Diebold et al.'s (2006) dynamic VAR model (DNS),[4] and Moench's (2008) affine FAVAR using the overall principal components as driving factors for the short rate (A-FAVAR). For each model, we choose the lag structure that minimizes the Bayesian information criterion (BIC). This results in first order specifications for every model, except the A-FAVAR, in all periods.

The A-FAVAR model employs the overall principal components as driving factors for the short rate. In particular, we assume as in Moench (2008) that

$$(6) \qquad \begin{pmatrix} F_t \\ r_t \end{pmatrix} = \mu + \Phi(L) \begin{pmatrix} F_t \\ r_t \end{pmatrix} + \omega_t,$$

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[3] The out-of-sample results of the random walk with a drift are considerably worse. Accordingly, we do not report them, though they are obviously available from the authors upon request.

[4] Diebold et al. (2006) estimate their VAR model using a Kalman filter. In contrast, we estimate the DNS model in two stages. We first extract the Nelson-Siegel factors and then estimate a VAR model by maximum likelihood estimation. This makes the results directly comparable to the other forecasting methods. It is nonetheless worth noting that using a Kalman filter yields a very similar forecasting performance.

where r_t denotes the short rate and ω_t is a vector of white noises with covariance matrix Ω. After estimating the parameters in (6), we impose no-arbitrage considerations by minimizing the market prices of risk (λ_0,λ_1) in

$$A_n = A_{n-1} + B'_{n-1}(\mu - \Omega\lambda_0) + {}^1\!/_2\, B'_{n-1}\Omega B_{n-1}$$

$$B_n = B'_{n-1}(\Phi - \Omega\lambda_1) - \delta',$$

for some initial conditions (A_0, B_0, δ). Next, we obtain the future values of the *n*-year zero rate using the affine nature of the model: $\hat{y}^{(n)}_{t+h|t} = -\frac{A_n}{n} - \frac{B'_n}{n}\hat{r}_{t+h|t}$.

We estimate every forecasting models using data from the first week of March 2007 to the last week of December 2011. We then assess forecasting performance for the remainder 156 weeks up to the last week of December 2014. To compute *h*-month ahead predictions, we iterate forecasts in real time by re-estimating the principal components, the Nelson-Siegel loadings and the model parameters each time we add one more week to the estimation window up to December 2014.[5]

Table 7 reports the mean absolute forecast error we obtain for each model across the different maturities and horizons. In contrast to Moench (2008), the A-FAVAR model does not compare well to the random walk for any horizon and maturity. Similarly, the DL-AR forecasts are reasonably good only at the 1-month horizon, though out-of-sample results are no better than the RW benchmark for longer horizons. This evidence is in line with de Pooter et al.'s (2010) findings that a VAR specification for the Nelson-Siegel factors displays a good performance only for short maturities and horizons. Finally, the DNS forecasts improve on the RW forecasts in the medium-run, reducing for instance the mean absolute forecast errors by up to 13% at the 1-year horizon.

Both NS-FAVAR models perform very well, improving forecasts by up to 15 bps at the 3-month horizon and by 15 to 50 bps at the horizons longer than 6-month. In particular, NS-FAVAR(fwrd) shows the best performance for any horizon longer than one month, irrespective of the maturity. It indeed fares very well, especially for the yields with medium and longer maturity, with decreasing relative mean absolute forecast errors. This suggests that forward-looking indicators are key to explaining the short- and medium-run movements in the yield curve. As a matter of fact, the AR and DL-AR models only outperform NS-FAVAR(fwrd) at the shortest horizon of one month and for

[5] See Marcellino et al. (2006) for an excellent discussion about the relative advantages and drawbacks of direct and iterated AR forecasts.

the shorter maturities. In turn, NS-FAVAR(all) not only entails lower mean absolute forecast errors relative to RW for the longer maturities, but also improves on the AR, DL-AR and A-FAVAR forecasts for every maturity.

These results are very promising. Diebold and Li (2006) and Moench (2008) show that their models provide better forecasts for the US yield curve than the random walk benchmark only at longer horizons, say, 6 months or more. Altavilla et al. (2004a,b) and Exterkate et al. (2013) are able to beat the random walk benchmark only at short horizons, though not for every maturity and not at longer horizons. In stark contrast, our NS-FAVAR models ameliorate the term structure forecasts for every maturity even at shorter horizons.

Next, we test whether these improvements are indeed statistically significant. To this end, we run a Model Confidence Set (MCS) analysis as in Hansen et al. (2011a). This procedure determines the number of superior models within a collection of alterative specifications given a confidence level. This number obviously depends on how informative the data are. If there is a lot of information in the data, the MCS analysis will select only a few, if not a single model. The main advantage of the MCS is that it is neither about comparing predictive ability against one single benchmark, nor about any other pairwise comparison. It treats the performance of every model in a symmetric way, attempting only to identify which models entail a better out-of-sample predictive power.[6]

Table 7 identify with stars the superior models for different horizons and maturities according to a block-bootstrap implementation of the MCS procedure, with blocks of 12 observations. We find that the NS-FAVAR models are among the best models at the 10% significance level for almost every maturity and horizon. In particular, the NS-FAVAR(fwrd) forecasts are usually superior for every maturity at any horizon longer than one-month ahead. The closer competitor is the NS-FAVAR(all), with a decent performance for any horizon longer than one month. It turns out that the random walk does not reveal itself as such a challenging benchmark. Finally, we fail to uncover at the usual significance levels any evidence of superior forecasting performance for the AR, A-FAVAR, DL-AR and DNS models at longer-than-1-month horizons.

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[6] The MCS procedure determines the number of superior models through a sequence of tests for the null hypothesis of equal predictive ability. The test statistic depends on the loss function of interest. In particular, we employ the conventional mean squared forecast error. The algorithm starts from a set M_0 of forecasting models and then test whether they have equal predictive ability. If the test rejects the null, we eliminate the model with poorest forecasting performance. We then repeat this procedure until we cannot reject anymore the null of equal predictive ability. To control the confidence level, Hansen et al. (2011a) suggest Gonçalves and White's (2005) moving-block bootstrap implementation. See Hansen et al. (2011b) for more details.

5. Robustness to different data frequency and span

This section reports the results of two robustness checks. First, we redo the analysis at the monthly frequency to make our results more comparable to the findings in the literature. Second, to increase the length of the out-of-sample period, we consider an alternative sample that starts in 2002. The price to pay for a longer time span is that we have to drop longer-term yields as well as some of the variables we use to extract diffusion indices.

For the monthly analysis, we consider the same data from Section 4, but looking only at the last week of each month. Table 8 reveals that the NS-FAVAR models have the best performance for virtually every yield for any horizon exceeding one month. At the 3-month horizon, the NS-FAVAR(fwrd) model shines for every maturity, apart from the 3-year yield. At the 6- and 9- month horizons, the NS-FAVAR models compete head to head. Whereas the NS-FAVAR(fwrd) has the best performance for the short-end of the yield curve, the NS-FAVAR(all) produces a lower mean absolute forecast error for longer-term yields. At longer horizons, the forecasting performance of the NS-FAVAR(fwrd) model is impressive, reducing the mean absolute forecast errors by 20 to 30% as compared to the RW benchmark. As expected, the extant models in the literature (A-FAVAR, DL-AR, and DNS) are superior to the simpler AR and RW alternatives only at longer horizons.

As for increasing the time span, recall that longer-term bonds exist only as from 2006, with liquidity picking up only in 2007. We thus restrict attention to shorter-term yields, with maturity up to 12 months, as in Vicente and Tabak (2008) and Faria and Almeida (2014). This allows us to increase significantly the time span, starting the sample period in 2002 rather than only in 2007. We have to drop, however, some of the macroeconomic indicators we employ to extract the diffusion indices. The list of variables in the appendix show that we have information since 2002 for only 113 of the 142 macroeconomic and financial indicators we consider. We initially estimate the model using data from January 2002 to December 2004, and then assess forecasting performance using data from January 2005 to December 2014.

Table 9 reports the out-of-sample results for the 1- to 12-month yields. The NS-FAVAR models remain dominant, comparing very well against the alternative forecasting models. Although the NS-FAVAR(fwrd) entails a higher predictive ability than the random walk for almost every yield at any forecast horizon, it outperforms the other forecasting models only for the short-end of the yield curve at longer-than-3-month horizons. In turn, the NS-FAVAR(all) works best for medium-term maturities at horizons superior to one month. Perhaps surprisingly, the dynamic Nelson-Siegel model entails the smallest mean absolute forecast errors for the shorter-term yields at the 1- and 3-month horizons. However, the DNS performance deteriorates considerably for longer horizons, obtaining the worst results for the 12-month-ahead forecasts. In turn, it is worth noting that the RW forecasts are significantly better than the other forecasts only for 6 and 12-month yields at the 1-month horizon.

6. Conclusion

This paper proposes to forecast future values of yields at different maturities by means of a FAVAR model for the level, slope and curvature of the yield curve. In particular, we estimate an augmented VAR model for a system that includes not only the Nelson-Siegel factors of the Brazilian yield curve, but also the principal components of a large number of macroeconomic and financial indicators. We show that our forecasting approach outperforms the extant models in the literature, including the random walk benchmark, even at shorter horizons. Further analysis reveals that using forward-looking state variables is vital to produce better forecasts.

We defer the assessment of external validity to future research. In particular, we plan to examine whether we indeed observe similar forecast improvements using US data. There is no reason to believe our findings automatically carry through. First, it is perhaps the case that the term structure of interest rates in Brazil has a very particular dynamics. Second, it is surprisingly easier to gather a larger number of forward-looking indicators in Brazil than in the US. This may hinder the predictive ability of the NS-FAVAR model given that market expectations about the economic and financial outlooks are very informative.

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Table 1

Principal components from the panel of 142 macro-financial indicators, full sample

Principal Components Analysis	correlation
Factor 1	
Latin America EMBI	0.901
Fed Funds rate	0.826
2-year treasury rate	0.813
3-month Libor	0.721
Expected trade balance annual change for the next 12 months	0.762
Factor 2	
Standard deviation of the 12-month industrial production forecast	-0.695
Standard deviation of the 12-month GDP growth forecast	-0.647
5-year US breakeven	0.659
Electric energy consumption - annual change	0.530
Expected consumer price inflation for the next month	0.501

This table reports the variables with the highest correlation with each of the principal components extracted from the panel of 142 macroeconomic and financial indicators.

Table 2

Principal components from the forward looking indicators, full sample

	correlation
Factor 1	
Latin America EMBI	0.946
Import growth for the next 12 months	-0.709
5-year US breakeven	-0.700
Trade balance annual change for the next 12 months	-0.630
3 months risk reversal USD/BRL	0.600
Factor 2	
Standard deviation of the 12-month industrial production forecast	0.727
Standard deviation of the 3-to-5-year primary budget balance forecast	0.707
Standard deviation of the 12-month service-sector GDP growth forecast	0.698
Standard deviation of the 12-month government debt forecast	0.686
Service-sector GDP growth in 3 to 5 years	0.631

This table lists the variables with the highest correlation with each of the first 2 principal components of the panel of forward-looking macroeconomic and financial variables.

Table 3
Policy rules based on factors

	PCA(all)	PCA(fwrd)
Constant	10.3413	11.3537
	(0.0874)	(0.0963)
first principal component	0.0599	0.2240
	(0.0881)	(0.0687)
second principal component	-0.1753	-0.5071
	(0.0959)	(0.0928)
R-square	0.083	0.126

This table documents factor-based rules for the target interest rate of the Central Bank of Brazil. We regress the target interest rate on the first and second principal components of the macroeconomic and financial variables we consider. We report two sets of coefficient estimates: PCA(all) uses the complete panel of 142 indicators, whereas PCA(fwrd) focuses only on forward-looking indicators. We also display robust standard errors in parentheses.

Table 4
Augmented Taylor rules

	(A)	(B)	(C)
Past target interest rate	0.983	0.950	0.955
	(0.003)	(0.011)	(0.010)
CPI forecast for the next 12 months	24.34	10.867	10.783
	(2.804)	(2.422)	(2.536)
GDP growth forecast for the next 12 months	15.924	4.282	4.609
	(3.257)	(1.120)	(1.131)
Predicted target interest rate based on PCA(all)		0.582	
		(0.101)	
Predicted target interest rate based on PCA(forward)			0.552
			(0.099)
R-square	0.968	0.969	0.969

This table reports the regression results for equation (5). Column (A) displays the coefficient estimates for the traditional Taylor rule, whereas columns (B) and (C) show the estimates for augmented Taylor rules that include the target interest rate predicted by the factor models in Table 3. We report robust standard errors in parentheses.

Table 5
Estimation of yields and principal components

		constant	PC1	PC2	SELIC	R-square
1-year	PCA(all)	0.100 (0.003)	0.010 (0.003)	-0.007 (0.002)	0.421 (0.069)	0.46
	PCA(fwrd)	0.112 (0.003)	0.006 (0.002)	-0.010 (0.001)	0.249 (0.049)	0.44
3-year	PCA(all)	0.109 (0.002)	0.011 (0.002)	0.002 (0.002)	0.377 (0.053)	0.53
	PCA(fwrd)	0.117 (0.002)	0.008 (0.002)	-0.004 (0.001)	0.230 (0.037)	0.44
5-year	PCA(all)	0.112 (0.002)	0.011 (0.002)	0.000 (0.002)	0.354 (0.049)	0.56
	PCA(fwrd)	0.118 (0.002)	0.008 (0.002)	-0.002 (0.001)	0.215 (0.035)	0.47
7-year	PCA(all)	0.113 (0.002)	0.011 (0.002)	0.000 (0.002)	0.344 (0.047)	0.57
	PCA(fwrd)	0.119 (0.002)	0.009 (0.002)	-0.001 (0.001)	0.208 (0.034)	0.49
10-year	PCA(all)	0.114 (0.002)	0.011 (0.002)	-0.001 (0.002)	0.337 (0.046)	0.57
	PCA(fwrd)	0.119 (0.002)	0.009 (0.002)	0.000 (0.001)	0.203 (0.033)	0.50

This table reports the estimation results for regressing interest rate yields on the first and second principal components of the macroeconomic and financial variables we consider as well as on the SELIC rate. We report two sets of coefficient estimates: PCA(all) uses the complete panel of 142 indicators, whereas PCA(fwrd) focuses only on forward-looking indicators. We also display robust standard errors in parentheses.

Table 6

Descriptive statistics for the in-sample absolute errors

	maturity	mean	std deviation	maximum	Date
NS-FAVAR(all)	1 year	0.09	0.14	1.13	24/06/2008
	2 years	0.07	0.09	0.58	28/12/2010
	5 years	0.08	0.09	0.60	21/10/2008
	7 years	0.10	0.10	0.86	21/10/2008
	10 years	0.12	0.12	1.13	21/10/2008
NS-FAVAR(fwrd)	1 year	0.09	0.14	1.14	24/06/2008
	2 years	0.07	0.09	0.59	28/12/2010
	5 years	0.09	0.09	0.63	21/10/2008
	7 years	0.10	0.10	0.84	21/10/2008
	10 years	0.12	0.12	1.11	21/10/2008

This table reports the sample mean, standard deviation and maximum values of the in-sample absolute errors (in percentage points) of the NS-FAVAR(all) and NS-FAVAR(fwd) for each maturity. We also display the data at which we observe the largest error in magnitude.

Table 7

Mean absolute forecast errors relative to random walk model

	RW	AR	A-FAVAR	DL-AR	DNS	NS-FAVAR(all)	NS-FAVAR(fwrd)
				1 month ahead			
12	0.395	0.840**	4.790	0.836**	0.932	0.806*	0.967
36	0.330	1.146	5.846	1.078	1.218	1.078	0.975*
60	0.376**	1.086	4.203	0.990	1.109	1.008	0.970*
84	0.424	0.996	3.674	0.901*	1.000	0.928**	0.955**
120	0.475	0.917	3.318	0.955	0.971	0.854*	0.945
				3 months ahead			
12	0.766	1.161	2.983	1.015	1.014	1.000	0.901*
36	0.757	1.214	3.047	1.010	1.029	0.962	0.844*
60	0.769	1.239	2.312	1.009	1.021	0.920	0.847*
84	0.778	1.245	2.316	1.009	1.017	0.900	0.872*
120	0.785	1.250	2.378	1.008	1.015	0.890*	0.902**
				6 months ahead			
12	1.253	1.343	2.054	1.001	0.982	1.107	0.894*
36	1.255	1.293	2.021	1.001	1.000	1.000	0.900*
60	1.277	1.247	1.442	1.001	1.015	0.954	0.883*
84	1.290	1.224	1.534	1.001	0.999	0.933	0.874*
120	1.301	1.207	1.614	1.001	0.984	0.919	0.868*
				9 months ahead			
12	1.748	1.333	1.486	0.995	0.943	1.087	0.844*
36	1.578	1.223	1.565	0.995	0.964	0.995	0.890*
60	1.599	1.123	1.145	0.997	0.962	0.920	0.831*
84	1.621	1.081	1.285	0.998	0.960	0.887	0.797*
120	1.640	1.051	1.365	1.000	0.958	0.864	0.773*
				12 months ahead			
12	1.519	1.133	1.539	0.995	0.870	1.011	0.759*
36	1.268	0.926	1.681	0.994	0.883	0.848	0.740*
60	1.268	0.837	1.275	0.993	0.876	0.754	0.664*
84	1.284	0.804	1.444	0.993	0.871	0.713	0.629*
120	1.297	0.784	1.555	0.994	0.870	0.689**	0.611*

The column RW displays the mean absolute forecast error (in percentage points) of the random walk benchmark, whereas the other columns report the mean absolute forecast error of each model relative to the random walk. We estimate every model using weekly data from March 2007 to December 2011 and then produce *h*-month ahead iterated forecasts, with *h* = 1, 3, 6, 9 and 12, for the period running from January 2012 to December 2014. NS-FAVAR(all) refers to the NS-FAVAR model with the principal components of the complete panel of macroeconomic and financial variables. NS-FAVAR(fwrd) considers the principal components based only on the forward-looking indicators. We identify the superior models at the 10% and 25% significance levels with * and **, respectively.

Table 8

Relative mean absolute forecast errors at the monthly frequency

	RW	AR	A-FAVAR	DL-AR	DNS	NS-FAVAR(all)	NS-FAVAR(fwrd)
				1 month ahead			
12	0.306*	1.436	1.858	1.796	1.155	1.014**	1.045
36	0.321*	1.125	1.857	1.797	1.109	1.157	1.145
60	0.330	0.957*	1.862	1.727	1.062	1.274	1.236
84	0.346	0.967*	1.946	1.718	1.043	1.369	1.328
120	0.358	0.964*	2.192	1.746	1.045	1.439	1.411
				3 months ahead			
12	0.724	1.115	1.348	1.253	1.113	0.802*	0.801*
36	0.710	1.339	1.413	1.339	1.177	0.939*	0.962**
60	0.697*	1.346	1.530	1.346	1.121	1.032**	0.985*
84	0.700**	1.347	1.800	1.347	1.087	1.099	0.967*
120	0.703	1.364	2.052	1.364	1.068	1.162	0.948*
				6 months ahead			
12	1.278**	0.986	1.076	1.091	1.144	1.026	0.942*
36	1.264**	1.121	1.114	1.121	1.130	1.009**	0.948*
60	1.276	1.135	1.176	1.135	1.069	0.924*	0.975
84	1.286	1.147	1.284	1.147	1.042	0.877*	0.955
120	1.295	1.159	1.388	1.159	1.023	0.838*	0.938
				9 months ahead			
12	1.822**	0.991	0.985	1.028	1.047	1.055	0.961*
36	1.669*	1.076	0.998	1.076	1.097	1.058	1.010**
60	1.665	1.061	1.047	1.061	1.039	0.958**	0.941*
84	1.669	1.062	1.120	1.062	1.004	0.897*	0.896*
120	1.675	1.063	1.183	1.063	0.977	0.853*	0.859*
				12 months ahead			
12	2.349	1.000	0.998	0.991	0.836	0.955	0.800*
36	2.137	1.036	0.995	1.036	0.863	0.902	0.839*
60	2.071	1.010	1.034	1.010	0.846	0.822	0.780*
84	2.044	0.988	1.107	0.988	0.831	0.770	0.740*
120	2.023	0.972	1.174	0.972	0.817	0.729	0.704*

The column RW displays the mean absolute forecast error (in percentage points) of the random walk benchmark, whereas the other columns report the mean absolute forecast error of each model relative to the random walk. We estimate every model using monthly data from March 2007 to December 2011 and then produce *h*-month ahead iterated forecasts, with *h* = 1, 3, 6, 9 and 12, for the period running from January 2012 to December 2014. NS-FAVAR(all) refers to the NS-FAVAR model with the principal components of the complete panel of macroeconomic and financial variables. NS-FAVAR(fwrd) considers the principal components based only on the forward-looking indicators. We identify the superior models at the 10% and 25% significance levels with * and **, respectively.

Table 9

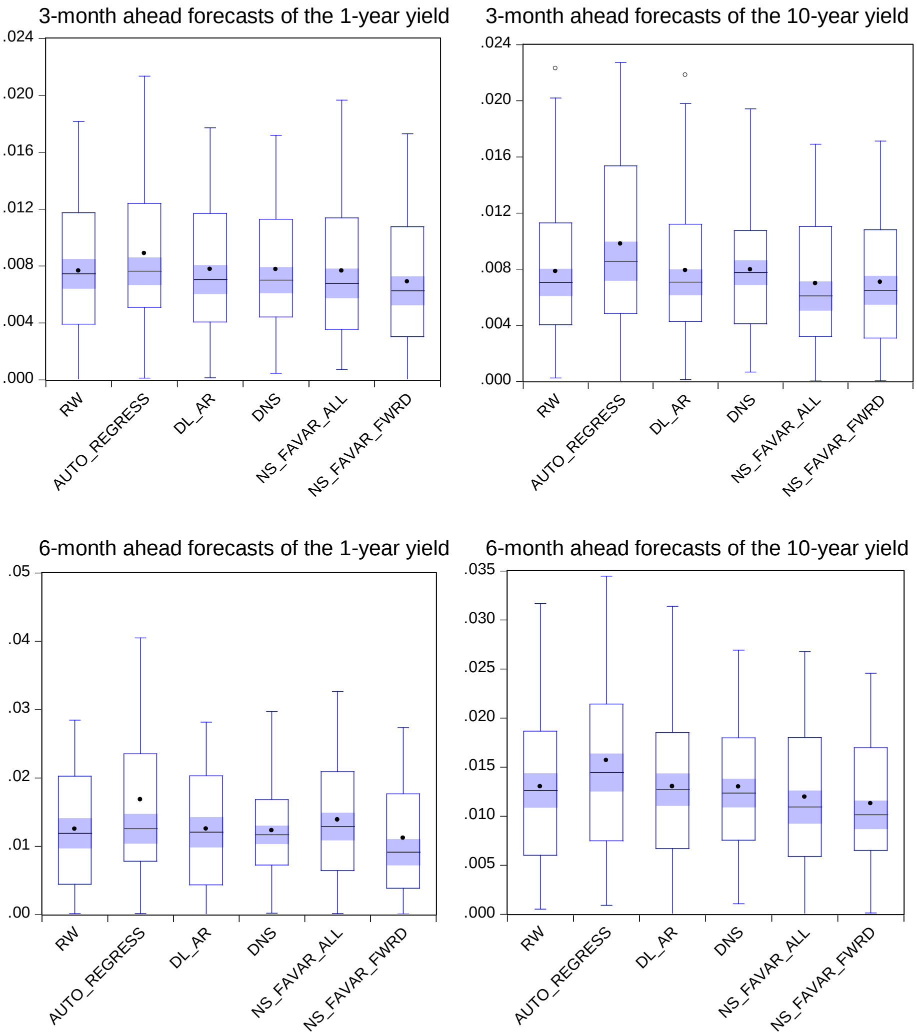
Mean absolute forecast errors relative to random walk model for the shorter-term yields

	RW	AR	A-FAVAR	DL-AR	DNS	NS-FAVAR (all)	NS-FAVAR (fwrd)
				1 month ahead			
1	0.246	1.054	1.285	1.510	0.743*	0.982	0.896
2	0.250	1.044	1.660	1.121	0.745*	0.924	0.856
3	0.256	1.037	2.164	1.227	0.836*	0.983	0.918
6	0.287*	1.024	3.257	1.419	1.074	1.125	1.108
12	0.334*	1.039	3.762	1.424	1.297	1.146	1.188
				3 months ahead			
1	0.760	1.163	1.295	1.140	0.701*	0.883	0.813
2	0.770	1.131	1.374	1.032	0.808*	0.918	0.869
3	0.780	1.105	1.503	1.064	0.943	0.934	0.902*
6	0.812*	1.059	1.796	1.120	1.126	0.993*	1.015**
12	0.858	1.040	2.033	1.110	1.354	0.928*	0.981
				6 months ahead			
1	1.451	1.357	1.171	1.056	0.833	0.812	0.768*
2	1.455	1.295	1.211	1.020	0.919	0.829	0.810*
3	1.457	1.249	1.277	1.035	1.000	0.843*	0.843*
6	1.485	1.139	1.370	1.038	1.196	0.838*	0.865
12	1.523	1.066	1.462	0.999	1.484	0.786*	0.818
				9 months ahead			
1	2.051	1.400	1.113	1.032	0.983	0.719	0.699*
2	2.046	1.339	1.148	1.026	1.046	0.739	0.724*
3	2.047	1.290	1.196	1.038	1.110	0.746**	0.740*
6	2.066	1.171	1.240	1.013	1.294	0.743*	0.765
12	2.093	1.072	1.308	0.956	1.612	0.746*	0.787
				12 months ahead			
1	2.471	1.410	1.131	1.002	1.178	0.676	0.654*
2	2.463	1.363	1.162	1.015	1.222	0.701	0.692*
3	2.464	1.314	1.199	1.026	1.272	0.717*	0.724**
6	2.465	1.190	1.245	1.007	1.449	0.747*	0.778
12	2.476	1.079	1.331	0.946	1.777	0.773*	0.814

The column RW displays the mean absolute forecast error (in percentage points) of the random walk benchmark, whereas the other columns report the mean absolute forecast error of each model relative to the random walk. We estimate every model using weekly data from March 2002 to December 2004 and then produce *h*-month ahead iterated forecasts, with *h* = 1, 3, 6, 9 and 12, for the period running from January 2005 to December 2014. NS-FAVAR(all) refers to the NS-FAVAR model with the principal components of the complete panel of macroeconomic and financial variables. NS-FAVAR(fwrd) considers the principal components based only on the forward-looking indicators. We identify the superior models at the 10% and 25% significance levels with * and **, respectively.

Figure 1

Box plots of the forecast errors for the 1- and 10-year yields at the 3- and 6-month horizons



Appendix: Data set

Name	Transf	Frequency	Release - lag	Period	Source
Financial					
1 month LIBOR rate	0	daily	0 day	0	Bloomberg
10 year treasury yield	1	daily	Real time	0	Bloomberg
12 months LIBOR rate	0	daily	0 day	0	Bloomberg
2 year treasury yield	0	daily	Real time	0	Bloomberg
3 months LIBOR rate	0	daily	0 day	0	Bloomberg
30 year treasury yield	3	daily	Real time	0	Bloomberg
Brazilian currency (BRL)	5	daily	Real time	0	Bloomberg
Brazilian stock market index (Ibov)	1	daily	Real time	0	Bloomberg
Federal funds target rate	0	daily	0 day	0	Bloomberg
Open interest on BRL	1	daily	1 day	1	BM&F Bovespa
Open interest on BRL - % banks	0	daily	1 day	1	BM&F Bovespa
Open interest on BRL - % brokers	0	daily	1 day	1	BM&F Bovespa
Open interest on BRL - % foreign investor	0	daily	1 day	1	BM&F Bovespa
Open interest on BRL - % foreign investor (future and exchange coupon)	0	daily	1 day	1	BM&F Bovespa
Open interest on BRL - % local and foreign investor	0	daily	1 day	1	BM&F Bovespa
Open interest on BRL - % local investor	0	daily	1 day	1	BM&F Bovespa
Open interest on Ibov	1	daily	1 day	1	BM&F Bovespa
Open interest on Ibov - % banks	0	daily	1 day	1	BM&F Bovespa
Open interest on Ibov - % foreign investor	0	daily	1 day	1	BM&F Bovespa
Open interest on Ibov - % local and foreign investor	0	daily	1 day	1	BM&F Bovespa
Open interest on Ibov - % local investor	0	daily	1 day	1	BM&F Bovespa
US Dollar index - log	3	daily	Real time	0	Bloomberg
Fiscal					
Budget result % of GDP for 3-5 years ahead	2	daily	Monday	0	Focus
Budget result % of GDP for 5 years ahead	2	daily	Monday	0	Focus
Budget result % of GDP for the next 12 months	3	daily	Monday	0	Focus
Government debt % of GDP for 3-5 years ahead	1	daily	Monday	0	Focus
Government debt % of GDP for 5 years ahead	1	daily	Monday	0	Focus
Government debt % of GDP for the next 12 months	3	daily	Monday	0	Focus
Primary budget result % of GDP for 3-5 years ahead	0	daily	Monday	0	Focus
Primary budget result % of GDP for 5 years ahead	0	daily	Monday	0	Focus
Primary budget result % of GDP for the next	0	daily	Monday	0	Focus

12 months

Forecast uncertainty					
Standard deviation of consumer price inflation for 3-5 years ahead projections	3	daily	Monday	0	Focus
Standard deviation of balance of payments surplus in US$ bn for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of balance of payments surplus in US$ bn for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of balance of payments surplus in US$ bn for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of consumer price inflation for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of consumer price inflation for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of export growth for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of export growth for 5 years ahead projections	3	daily	Monday	0	Focus
Standard deviation of export growth for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of GDP growth for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of GDP growth for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of GDP growth for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of GDP services sector growth for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of GDP services sector growth for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of GDP services sector growth for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of general price inflation for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of government debt % of GDP for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of government debt % of GDP for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of government debt % of GDP for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of import growth for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of import growth for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of import growth for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of industrial production growth for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of industrial production growth for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of industrial production growth for the next 12 months projections	1	daily	Monday	0	Focus

Standard deviation of primary budget result % of GDP for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of primary budget result % of GDP for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of primary budget result % of GDP for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of trade balance growth for 3-5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of trade balance growth for 5 years ahead projections	1	daily	Monday	0	Focus
Standard deviation of trade balance growth for the next 12 months projections	1	daily	Monday	0	Focus
Standard deviation of wholesale price inflation for the next 12 months projections	1	daily	Monday	0	Focus
Inflation					
Agriculture commodity index (S&P) - annual change	4	daily	Real time	0	Bloomberg
Commodity index (S&P) - annual change	5	daily	Real time	0	Bloomberg
Consumer price for the city of Sao Paulo- monthly change	1	weekly	1 week	0	FIPE
Consumer price inflation for 3-5 years ahead - median	3	daily	Monday	0	Focus
Consumer price inflation for 5 years ahead - median	2	daily	Monday	0	Focus
Consumer price inflation for the next 12 months - average	2	daily	Monday	0	Focus
Consumer price inflation for the next 12 months - median	2	daily	Monday	0	Focus
Daily consumer price - monthly change	1	daily	1 day	1	FGV
Daily consumer price - monthly change for the last 7 days	1	daily	1 day	1	FGV
Daily food consumer price - monthly change	1	daily	1 day	1	FGV
Energy commodity index (S&P) - annual change	4	daily	Real time	0	Bloomberg
Expected consumer price for the current month - monthly change	1	daily	Monday	0	Focus
Expected consumer price for the next month - monthly change	1	daily	Monday	0	Focus
Food consumer price for the city of Sao Paulo- monthly change	0	weekly	1 week	1	FIPE
Food producer price - monthly change	0	daily	1 day	1	CEASA
Food producer price - monthly change for the last 7 days	0	daily	1 day	1	CEASA
Food producer price with CPI weighting- monthly change	0	daily	1 day	1	CEASA
General price inflation for the next 12 months	1	daily	Monday	0	Focus
General price inflation for the next for 3-5 years ahead - median	1	daily	Monday	0	Focus
General price inflation for the next for 5 years ahead - median	1	daily	Monday	0	Focus
Metal commodity index (S&P) - annual change	5	daily	Real time	0	Bloomberg
US Breakeven for 2 year	1	daily	Real time	0	Bloomberg
US breakeven for 5 year	0	daily	Real time	0	Bloomberg

Vegetables producer price - monthly change	0	daily	1 day	1	CEASA
Vegetables producer price - monthly change for the last 7 days	0	daily	1 day	1	CEASA
Wholesale price inflation index for 3-5 years ahead - median	1	daily	Monday	0	Focus
Wholesale price inflation index for 5 years ahead - median	1	daily	Monday	0	Focus
Wholesale price inflation index for the next 12 months	1	daily	Monday	0	Focus
Real activity					
Balance of payments surplus in US$ bn for 3-5 years ahead	0	daily	Monday	0	Focus
Balance of payments surplus in US$ bn for 5 years ahead	0	daily	Monday	0	Focus
Balance of payments surplus in US$ bn for the next 12 months	3	daily	Monday	0	Focus
Barclays economic suprise index - United States	0	daily	1 day	0	Bloomberg
Citi economic suprise index - Asia ex Japan	0	daily	1 day	1	Bloomberg
Citi economic suprise index - Latin America	0	daily	1 day	1	Bloomberg
Daily eletricity consumption	4	daily	2 days	0	ONS
Daily eletricity consumption in North States	5	daily	2 days	0	ONS
Daily eletricity consumption in Northeast States	4	daily	2 days	0	ONS
Daily eletricity consumption in South States	4	daily	2 days	0	ONS
Daily eletricity consumption in Southeast States	4	daily	2 days	0	ONS
Europe economic suprise index - Europe	0	daily	1 day	0	Bloomberg
Export growth for 3-5 years ahead	1	daily	Monday	0	Focus
Export growth for 5 years ahead	1	daily	Monday	0	Focus
Export growth for the next 12 months	1	daily	Monday	0	Focus
Factors conditioning the monetary base - Banking reserves as % of M1	0	daily	20 days	0	BCB
Factors conditioning the monetary base - External sector operations as % of M1	0	daily	20 days	0	BCB
Factors conditioning the monetary base - National treasury as % of M1	3	daily	20 days	0	BCB
Factors conditioning the monetary base - Operations with federal securities as % of M1	0	daily	20 days	0	BCB
GDP growth for 3-5 years ahead	3	daily	Monday	0	Focus
GDP growth for 5 years ahead	1	daily	Monday	0	Focus
GDP growth for the next 12 months	1	daily	Monday	0	Focus
GDP services sector growth for 3-5 years ahead	2	daily	Monday	0	Focus
GDP services sector growth for 5 years ahead	2	daily	Monday	0	Focus
GDP services sector growth for the next 12 months	3	daily	Monday	0	Focus
Import growth for 3-5 years ahead	3	daily	Monday	0	Focus
Import growth for 5 years ahead	1	daily	Monday	0	Focus
Import growth for the next 12 months	1	daily	Monday	0	Focus

Industrial production growth for 3-5 years ahead	2	daily	Monday	0	Focus
Industrial production growth for 5 years ahead	2	daily	Monday	0	Focus
Industrial production growth for the next 12 months	1	daily	Monday	0	Focus
International reserves	5	daily	1 day	1	BCB
Money supply - Currency outside banks as % of M1	2	daily	20 days	0	BCB
Money supply - Demand deposits as % of M1	2	daily	20 days	0	BCB
Money supply - M1	5	daily	20 days	0	BCB
Trade balance growth for 3-5 years ahead	0	daily	Monday	0	Focus
Trade balance growth for 5 years ahead	0	daily	Monday	0	Focus
Trade balance growth for the next 12 months	0	daily	Monday	0	Focus
Risk					
Bloomberg Asia ex Japan financial conditions index	0	daily	Real time	0	Bloomberg
Bloomberg Eurozone financial conditions index	0	daily	Real time	0	Bloomberg
Bloomberg US financial conditions index	0	daily	Real time	0	Bloomberg
BRL risk reversal for options of 1 month	1	daily	Real time	1	Bloomberg
BRL risk reversal for options of 3 months	1	daily	Real time	1	Bloomberg
Credit default swap - Brazil	1	daily	Real time	0	Bloomberg
Credit default swap - Latin America	1	daily	Real time	1	Bloomberg
JPMorgan emerging market bond index	3	daily	1 day	1	JP Morgan
JPMorgan emerging market bond index - Brazil	1	daily	1 day	0	JP Morgan
JPMorgan emerging market bond index - ex Brazil and Argentina	1	daily	1 day	1	JP Morgan
JPMorgan emerging market bond index - Latin America	1	daily	1 day	0	JP Morgan
TED spread - LIBOR minus T-bills (3 months)	0	daily	0 day	0	Bloomberg
VIX	1	daily	Real time	0	Bloomberg

The transformation codes are 0 - stationary, 1 - stationary with drift, 2 stationary with drift and trend, 3 stationary at first difference. Regarding to data span: 0 - since 2002; 1 - only after March 2007.