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Abstract: How often should we update predictions for economic activity? Gross domestic product is a quarterly variable disseminated usually a couple of months after the end of the quarter, but many other macroeconomic indicators are released with a higher frequency, and financial markets react very strongly to them. However, most of the professional forecasters, including the IMF, the OECD, and most central banks, tend to update their forecasts of economic activity only two to four times a year. The main exception is the Central Bank of Brazil which is responsible for collecting and publishing a daily survey on GDP and other variables. The aim of this article is to evaluate the forecasting performance of the Central Bank of Brazil Survey and to compare it with the mechanical forecasts based on state-of-the-art nowcasting techniques. Results indicate that institutional forecasts perform as well as model-based forecasts. The latter finding suggests that, on the one hand, judgmental forecasters do not have computational limitations and are able to incorporate very quickly new information in a way that is as efficient as a machine. On the other hand, it confirms what has been found in other studies, namely that a linear time invariant model does a good job and hence that eventual nonlinearities, time variations and soft information (such as weather conditions or government decisions) that could be incorporated by judgment, do not provide new important information.

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1 Introduction

Monitoring short-term economic developments, in particular real GDP growth, is the instrument through which market participants and policy institutions all over the world make their decisions on how to invest or on how to conduct monetary and fiscal policy. Real GDP growth in many countries, including Brazil, is a quarterly variable that is released by the national statistical office with a delay that could be, at times, significant. In the case of Brazil the delay is two months. In other words, real GDP growth related to the first quarter (January to March) is disclosed only in May.

Given this limitation it is nevertheless reasonable to think that it is possible to learn the current economic condition by monitoring other indicators that are linked to GDP growth and that are released at a higher frequency. Newspapers, statistical offices, and central bank websites release daily data (for instance releases on industrial production, on the number of vehicles sold, on the confidence of consumers, etc.) that can be used to produce early estimates of GDP growth. Market participants monitor these data too. Global information services, such as Bloomberg and Forex Factory, report a calendar of data releases that is highly regarded by the markets. Bloomberg and Forex Factory also assign a measure of importance to each release, which reflects the usage by markets. Bloomberg, in addition, conducts a survey and collects forecasts from analysts and economists on each release they report and publishes it the day before the release is disseminated.

Academia has also moved toward incorporating this more timely information into formal econometric forecasting models. Two seminal papers (Evans, 2005, and Giannone et al., 2006) have modeled, within the same statistical framework, the joint dynamics of GDP and the monthly indicators. According to this literature, it is worth while to update economic predictions often, as the incorporation of the continuous data flow makes the forecasts more and more accurate.

Professional forecasters, however, do not publish short-term economic forecasts frequently. The Organisation for Economic Co-operation and Development (OECD) and the International Monetary Found (IMF) report their forecast twice a year, many central banks (e.g. Bank of

England, Bank of Canada, and the Federal Reserve Open Market Committee) four times a year and, only a few institutions update their forecasts monthly (e.g. Banque de France, Bank of Japan, Bundesbank, the Conference Board). The process through which they revise their forecasts is not clear.

The Central Bank of Brazil (BCB), though, is an exception to this framework. It is, in fact, responsible for the set up of an interesting Market Expectation System, a web interface where financial institutions, consulting firms, and universities report their expectations for various macroeconomic variables including GDP.

The aim of this paper is to understand how sensible it is for an institution, such as the BCB, to produce such regular predictions of GDP growth. The aim is to evaluate the forecasting performance of the BCB Survey and to compare it with the mechanical forecasts based on state-of-the-art nowcasting techniques.

Results indicate that market participants' predictions are well behaved, i.e. as more information becomes available their accuracy and correlation with the out-turn increases.

In addition, it turns out that institutional forecasts perform as well as model-based forecasts. The latter result suggests that, on the one hand, judgmental forecasters do not have computational limitations and they are able to incorporate very quickly new information in a way that is as efficient as a machine. On the other hand, it confirms what has been found in other studies, namely that a linear time invariant model does a good job and hence that eventual non linearities, time variations, and soft information (such as weather conditions or government decisions) that could be incorporated by judgment, do not provide new important information. According to this last result, the often-cited superiority of professional forecasts (see Ang et al., 2007, Clements, 2010, Jansen et al., 2012) turns out to be weak in our sample confirming findings in Giannone et al. (2006) and Liebermann (2011).

Recently, there has been a lot of interest in applying this statistical environment to various economies, including the United States (Lahiri and Monokroussos, 2013), the Euro Area (Angelini et al., 2010; Angelini et al., 2011; Camacho and Perez-Quiros, 2010), France (Barhoumi et al., 2010), Germany (Marcellino and Schumacher, 2010), Ireland (D'Agostino et al., 2008;

Liebermann, 2012), the Netherlands (de Winter, 2011), the Czech Republic (Arnostova et al., 2011; Rusnák, 2013), New Zealand (Matheson, 2010), Norway (Aastveit and Trovik, 2012), Switzerland (Siliverstovs, 2012) and for China (Yiu and Chow, 2010). For a survey, see Bańbura et al. (2012) and Bańbura et al. (2013).

In the case of Brazil, Issler and Notini (2013) propose an interpolation method based on state-space models to estimate monthly Brazilian GDP, through the use of coincident indicators. This methodology is part of to the literature on coincident indicators of economic activity, where an unobserved state of the economy is estimated from a multivariate model. Chauvet (2001) constructs an indicator of Brazilian monthly GDP through the use of a Markov switching dynamic factor model. In this article, instead, we aim at pure nowcasting, defined as timely estimation of GDP.

The rest of the paper is structured as follows. Section 2 describes the structure of the data releases in Brazil. Section 3 introduces the model and estimation technique. Section 4 describes the BCB survey and the other benchmarks. Section 5 introduces the empirical analysis and comments on the results. Section 6 concludes.

2 The Data Set

The Brazilian statistical office publishes real GDP growth two months after the end of the quarter. The aim of the statistical model we propose in this paper is to predict GDP before the official figures are published by taking advantage of the information in the flow of economic data releases that precede them and updating our prediction with each successive data release.

We include in our model those variables whose headline number is reported by the main statistical sources and central banks; in addition we consider those indicators monitored by financial markets and by the press. We choose the transformations that guarantee stationarity of the variables (see Table 1), which are the same as the ones reported by the media and Bloomberg, making the comparison easier.[4] We consider only real data and surveys. We disregard prices and financial variables, nominal variables, and sector-specific series. This choice reflects the results of previous research, in which the inclusion of these variables does not improve the model's forecasting performance (see Bańbura and Modugno, 2010, and Bańbura et al., 2012).[5]

Table 1 reports some details on the selected series, in particular the timing of the release and the importance that the financial markets attach to the series, according to the Bloomberg index. The peculiarity of the Brazilian data set is the fact that it includes two indicators that are strictly related to the target variable (quarterly GDP). The first is the monthly nominal GDP, published by the BCB, based on monthly indicators for economic activity and prices. The second is the economic activity index (EAI), also published by the BCB. The EAI is a monthly coincident indicator based on the same methodology used to measure the Brazilian quarterly GDP, which

[4]Most of the variables are in month-on-month (MoM) change in order to guarantee stationarity, with the exception of Registered Jobs Created which is a yearly change to account for seasonality issues given that the variable is not seasonally adjusted, PMI Manufacturing is in levels but behaves like a MoM change for how it is constructed and Real GDP is the target variable and it is quarter-on-quarter (QoQ).

[5]It is true that financial variables, which are available at very high frequency might, in principle, carry information on expectations of future economic developments (Andreou et al., 2008), however we only consider macro indicators and surveys given that other studies on this topic - see Bańbura et al. (2013), Stock and Watson (2005) and Forni et al. (2003) - indicate that "financial variables do not help improving the precision of GDP now-cast", because the news from financial variables is highly volatile and leads to revisions in different directions. Moreover, Bańbura et al. (2013) show that there is correlation between some financial variables and GDP, but only at low frequency: this indicates that while financial variables are not important for short term forecast they could instead be important for long term forecast. This is also confirmed by the fact that market participants mostly monitor real variables.

Table 1: *Series used in the model*

Name	Timing	Publishing lag	Frequency	Source	Starting Date	Transf.	Relevance Bloomberg
Registered jobs created	20^{th} month	20 days	M	MTE	May-99	Yearly change	-
Formal employment	20^{th} month	20 days	M	IBGE	Jan-85	Monthly change	63.5
Merchandise exports	first days	2 days	M	MDIC	Jan-54	MoM	40.4
Merchandise imports	first days	2 days	M	MDIC	Jan-59	MoM	36.5
Capacity utilization	first week	one month	M	CNI	Dec-91	Monthly change	32.7
Industrial production	first days	one month	M	IBGE	Jan-91	MoM	90.4
Consumer confidence index	last week	current month	M	FGV	Sep-05	Monthly change	17.3
Economic activity index	middle	1-2 months	M	BCB	Jan-03	MoM	23.2
Monthly GDP	end	one month	M	BCB	Mar-90	MoM	-
Manufacturing sales	first days	one month	M	CNI	Dec-91	MoM	-
PMI manufacturing	first days	2 days	M	BancoRl	Feb-06	Levels	75.0
Extended retail trade	middle	1-2 months	M	IBGE	Jan-03	MoM	-
Retail trade: volume	middle	1-2 months	M	IBGE	Jan-03	MoM	71.1
Real GDP	first days	2 months	Q	IBGE	Q1-90	QoQ	80.1

Notes. Timing: is approximately the number of days from the end of the reference period; **Frequency:** indicates whether the series is monthly (M) or quarterly (Q); **Sources:** MTE (Ministério do Trabalho e Emprego), IBGE (Fundaçâo Instituto Brasileiro de Geografia e Estatística), MDIC (Ministério do Desenvolvimento, Indústria e Comércio Exterior), CNI (Confederaçâo Nacional da Indústria), FGV (Fundaçâo Getúlio Vargas), BCB (Banco Central do Brasil), BancoRL (Banco Real); **Bloomberg:** reports the market relevance of each variable according to Bloomberg's relevance index, that ranges from 0 to 100.

consists of a set of proxies of economic behavior in the different economic sectors (agriculture, industry, distributive trade, transportation, services). As the EAI is a recent indicator, it still does not relate directly to the monthly nominal GDP, whose calculations follow an older methodology.

The rest of the variables can be divided into four categories: surveys, labor, production/demand, and trade indicators. Among surveys, we consider the consumer confidence index and the purchasing manager index (PMI). The consumer confidence index is very timely and it is the only piece of information in Brazil published within the reference period, though Bloomberg does not rank it as important (17.3%). The PMI is released at the beginning of the following month and is a relevant series according to the markets (75.0%).

For labour, we include registered jobs created (RJC) and formal employment (FE). The latter is rated fairly important by Bloomberg (63.5%). Both variables are timely. For production, we track industrial production (IP), which is rated highly for importance by Bloomberg (90.4%). For domestic demand, we track capacity utilization (CU), real manufacturing turnover (RMT), extended retail trade (ERT) and retail trade (RT). ERT, differently from RT, reports the volume of sales of formally established companies with 20 or more employed persons and whose main activity is retail trade which includes "Vehicles, motorcycles, parts and accessories" and

"Construction material". Bloomberg comments RT and rates it fairly high in terms of importance (71.1%). The trade category is particularly important for the Brazilian economy given its timeliness. Exports and Imports have the same publication lag as the PMI.

Most of the hard data series (employment, retail sales and industrial production) are published with a three to six weeks lag after the end of the reference month. Trade variables (exports and imports) are published at the beginning of the following month. Differently from other countries the statistical office, the Brazilian Institute of Geography and Statistics (IBGE), disseminates a monthly GDP indicator, which is published four weeks after the reference period.

3 The Nowcasting Problem and the Econometric Framework

The problem of nowcasting lies in estimating GDP in the interval of time between the beginning of the reference quarter and its official release, exploiting the information coming from other higher frequency variables[6].

More formally, the nowcast of GDP (y_t^Q) can be defined as the orthogonal projection of y_t^Q on the available information set Ω_v, which contains mixed-frequency variables (x_j) and is characterized by a "ragged edge" structure given that the time of the last available information varies from series to series.

Each time new information arrives, a new nowcast is produced. This nowcast can be decomposed as follows:

$$E[y_t^Q|\Omega_{v+1}] = E[y_t^Q|\Omega_v] + E[y_t^Q|I_{v+1}]. \tag{1}$$

The new forecast $E[y_t^Q|\Omega_{v+1}]$ is just the sum of the old forecast $E[y_t^Q|\Omega_v]$ and the revision $E[y_t^Q|I_{v+1}]$, where

$$I_{v+1} = x_j - E[x_j|\Omega_v]. \tag{2}$$

[6]In this section we closely follow Giannone et al., 2006; Bańbura Modugno, 2010; Bańbura et al., 2012; and Bańbura et al., 2013.

This revision (I_{v+1}) is the expected value of our target variable conditional to the difference between the actual release of any variable $(x_j \in \Omega_{v+1})$ and what our model was predicting for that release $(E[x_j|\Omega_v])$. The only element that leads to a change in the nowcast is the "unexpected" (with respect to the model) part of the data release, I_{v+1}, which we call the "news".

As shown by Bánbura and Modugno (2010), the magnitude of the forecast revision depends both on the size of the news and on its relevance for the target variable. Through this interesting mechanism, it is possible to trace the contribution of each series to the revision of the nowcast, in particular putting in relation the revision of the target with the unexpected developments of the inputs.

The model we use in order to compute the nowcast and the news is a dynamic factor model (DFM). This model produces a good representation of the data and guarantees, at the same time, parsimony. It exploits the fact that there is a large amount of co-movement among macroeconomic data series, and hence that relatively few factors can explain the dynamics of many variables (see Sargent and Sims, 1977; Giannone et al., 2005; Watson, 2004; and Stock and Watson, 2011).

The model can be written as a system with two types of equations: a measurement equation (Equation 3) linking the observed series (i.e GDP and all the indicators listed in Table 1) to a latent state process, and the transition equation (Equation 4), which describes the state process dynamics. Equations 3 and 4, written in a state space form, allow the use of the Kalman filter to obtain an optimal projection for both the observed and the state variables. The Kalman filter generates projections for all of the variables in the model (GDP but also all the other data releases).

The DFM model is described by the following equations:

$$y_t = \Lambda f_t + e_t, \tag{3}$$

$$f_t = A_1 f_{t-1} + A_2 f_{t-2} + ... + A_p f_{t-p} + u_t \qquad u_t \sim i.i.d.N(0, Q), \tag{4}$$

$$e_{i,t} = \rho_i e_{i,t-1} + v_{i,t} \qquad\qquad v_{i,t} \sim i.i.d.N(0, \sigma_i^2), \tag{5}$$

where $y_t = [y_{1,t}; y_{2,t}; ...; y_{n,t}]'$ denotes a set of standardized stationary monthly variables, f_t is a vector of r unobserved common factors with zero mean and unit variance, Λ is a matrix of coefficients collecting the factor loadings for the monthly variables, and $e_t = [e_{1,t}; e_{2,t}; ...; e_{n,t}]'$ is a n-dimensional vector of idiosyncratic components uncorrelated with f_t at all leads and lags.

This last assumption, which means that all of the joint correlation between observables is explained by the common factors, is strong and unrealistic, however Doz et al. (2006) have shown that the effects of this mispecification on the estimation of the common factors is negligible for large sample size (T) and the cross-sectional dimension (n).

We consider only one factor and two lags in Equation 4 and an AR(1) process for the idiosyncratic components described in Equation 5.[7]

In order to incorporate quarterly variables into the model, we construct for each of them a partially observed monthly counterpart in which the value of the quarterly variable is assigned to the third month of the respective quarter. We assume that the "unobserved monthly" growth rate of GDP (y_t^{UM}) admits the same factor model representation as the monthly real variables:

$$y_t^{UM} = \Lambda_Q f_t + e_t^Q, \tag{6}$$

$$e_t^Q = \rho_Q e_{t-1}^Q + v_t^Q \qquad\qquad v_t^Q \sim i.i.d.N(0, \sigma_Q^2). \tag{7}$$

To link y_t^{UM} with the observed GDP data, we construct a partially observed monthly series and we use the approximation of Mariano and Murasawa (2003):

$$y_{i,t}^Q = y_{i,t}^{UM} + 2y_{i,t-1}^{UM} + 3y_{i,t-2}^{UM} + 2y_{i,t-3}^{UM} + y_{i,t-4}^{UM}. \tag{8}$$

The estimation procedure is quasi maximum likelihood. As shown in Doz et al. (2006), the

[7]We use Bai Ng (2002) Information Criteria to select the number of factors in Equation 3 and Akaike Information Criteria to select the lag order of Equation 4. See the appendix for details.

estimator, apart from being robust to model mispecification, is feasible when n is large (as in the case of Brazil) and easily implementable using the Kalman smoother and the EM algorithm, initialized using principal components, as in traditional factor analysis.

Given that most of the indicators we include in our model are characterized by missing data at the beginning of the sample (as it is in the case of the consumer confidence index, which starts in September 2005, or the PMI, which starts in February 2006) and by a "ragged edge" structure, due to unsynchronized data releases at the end of the sample, we adapt the estimation procedure to the presence of arbitrary patterns of missing data following Bańbura and Modugno (2014).

4 The BCB Survey and Other Benchmarks

The BCB has set up a Market Expectation System, a web interface where financial institutions, consulting firms, and universities, which are required to have a specialized team on macroeconomic projections, report their expectations for various macroeconomic variables including GDP growth. The process through which these institutions revise their forecasts is not clear, nevertheless it is reasonable to think that these predictions are not entirely model based, but that a certain amount of judgment is also used.[8] Every business day at 5:00 pm (GMT-2) the information is consolidated and several statistics are generated: averages, medians, standard deviations, coefficients of variation, and minimum and maximum values of the projections recorded by the participants. Of the universe of qualified institutions, most of them alter their expectations weekly. For the purposes of our exercise, we consider the median projection.

The other important benchmark we consider is Bloomberg, which conducts a survey and collects forecasts from analysts and economists in order to produce predictions for GDP and other market-relevant variables before their release dates. Bloomberg publishes predictions as soon as they have at least three respondents to their questionnaire, which is generally around two weeks before the release of the relevant data series. Thereafter the prediction is continually

[8]This statement was confirmed by a BCB forecasting expert.

revised until 24 hours before the release. The final number is usually close to the actual release value.

Surveys of professional forecasters are averages and according to the literature on forecast combination should have the advantage of performing better than single forecasts (see Bates and Granger, 1969; Diebold and Lopez, 1996; Newbold and Harvey, 2002; and Clements and Hendry, 2004). In addition, short term forecasts, produced by the surveys, are based on real-time information.

We also consider as benchmarks the OECD, IMF (released twice a year), and the BCB quarterly forecasts to compare the model results on calendar year forecasts.

5 Model Evaluation

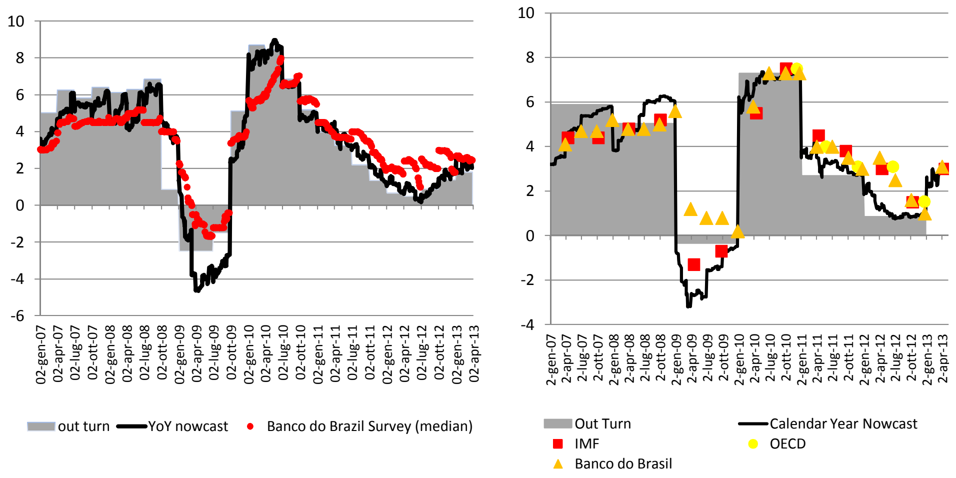
In order to evaluate the performance of the model we report a "pseudo real time" historical reconstruction from 2007:Q1 to 2013:Q1. We estimate the model recursively and we take account of information from each new data release (real-time), but we do not consider revisions (pseudo).[9] This last point can in principle distort the results in favour of the model, given that the BCB short term forecasts and the Bloomberg survey rely on real time information. However, given the robustness of factor models to data revision errors (see Giannone et al., 2006 and Bańbura et al., 2013), we expect this not to be the case.

The results of the historical evaluation are reported in the figures below. Figure 1 compares both the year-on-year GDP nowcast with the BCB Survey (panel a) and the calendar year nowcast with the IMF and OECD forecasts (panel b).

Figure 2 compares the root-mean-squared forecast error (RMSFE) of the model - on average for all of the calendar quarters in the historic reconstruction period - with the short-term forecast of BCB, the Bloomberg's survey of independent forecasters (published the day before the preliminary GDP release) and an auto-regressive forecast, which changes only when GDP

[9] We cannot conduct a real time analysis given that we do not have real time information for all the data series included in the model. To our knowledge only the OECD reports real time information on Brazil, but only on a small number of series, namely GDP, industrial production, retail trade, export and import. See http://stats.oecd.org/mei/default.asp?rev=1.

Figure 1: GDP nowcast



a) YoY Nowcast

b) Calendar Year Nowcast

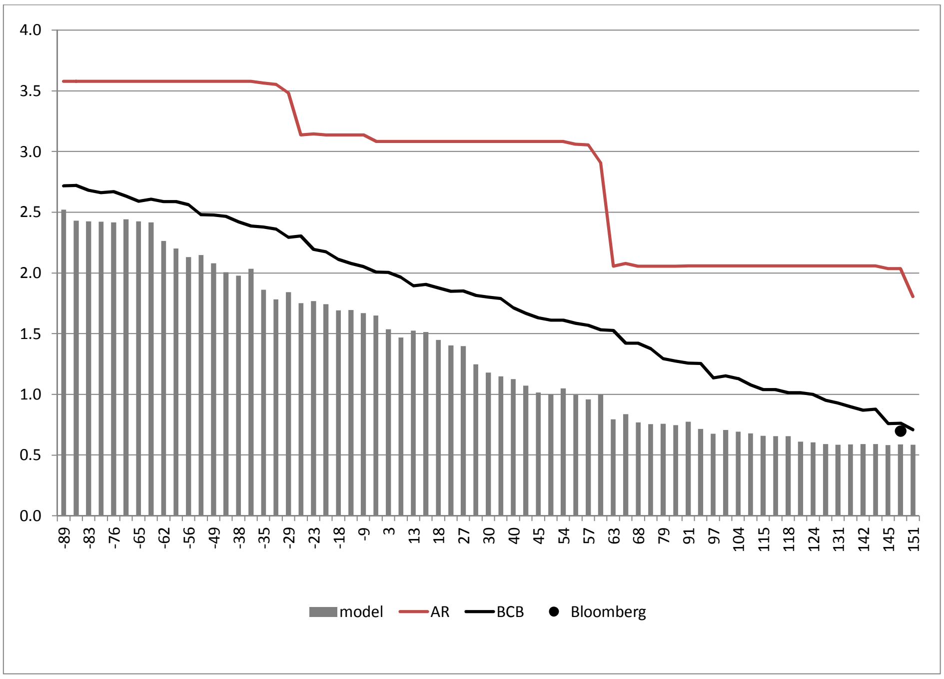
Notes. Comparison between GDP nowcast, GDP actual value, and the BCB survey. Panel a reports the YoY growth rate, panel b the calendar year.

is released. Given that the BCB GDP Survey reports YoY figures, we evaluate the model on a YoY basis. Results do not differ significantly if we consider QoQ figures.

The model's quarterly GDP growth prediction is first made 90 days before the start of a given quarter. It is then updated with each successive data release until the release of preliminary GDP, which takes place 145 days after the start of the calendar quarter. Thereby for each calendar quarter there is a period of 235 days (the "prediction period") over which the prediction is continuously updated. This period is measured by the X-axis. The Y-axis measures the root-mean-squared forecast error (RMSFE) for each different series of predictions.

In Table 2, we report the RMSFE reduction by release, in each of the three months of the reference quarter. Specifically, real GDP, Exports, industrial production, PMI and formal employment are the data releases that have the most impact in improving the accuracy of the

Figure 2: RMSFE



Notes. The Y-axis reports the root-mean-squared forecast error (RMSFE) over the period 2007:Q1 to 2013:Q1. The forecast accuracy is evaluated from the first month of the previous quarter to the time when GDP is released. The X-axis reports the distance in terms of days from the beginning of the current quarter.

Table 2: *Average MSFE Reduction by Variable*

	m1	m2	m3
Merchandise exports	-0.5	-21.8	4.9
Merchandise imports	0.0	-1.1	-0.9
PMI manufacturing	7.4	-23.5	-10.9
Industrial production	-34.1	-14.9	-3.9
Manufacturing sales	-4.8	-1.9	4.8
Capacity utilization	-5.3	1.9	0.9
Economic activity indicator	-7.0	-6.4	-0.9
Extended retail trade	-7.1	-4.3	-5.6
Retail trade: volume of sales	-1.6	-0.5	-0.7
Registered jobs created	-6.1	-11.7	-2.5
Formal employment	-17.7	-11.5	-0.5
Consumer confidence index	-1.0	-0.5	0.0
Monthly GDP	-2.0	10.3	-0.5
Real GDP			-42.5

Notes. These results are referred as the first (m1), second (m2), and third (m3) months of the nowcast period.

model's prediction.

5.1 Tests

The BCB professional forecasts seem to be highly collinear with the nowcasts and equally accurate. In Table 3, we report the Diebold-Mariano (2002) test of equal predictive accuracy to check whether the difference in forecasting performance between models is significant. For each month, we report the sample average of the difference between the squared errors of the AR and the BCB professional forecasts both with respect to the nowcasting model (benchmark), in coincidence with the first Brazilian release (exports). We report the value of the DM test and its standard deviation estimated using heteroskedasticity and autocorrelation robust (HAC) standard errors (see appendix A.2 for details). The test confirms better performance in terms of accuracy of the nowcasting model in comparison with the AR (in the forecast, nowcast and backcast) and a slightly better performance in comparison with the BCB forecasts (only in the second and third month of the nowcast and in the backcast).

From Figure 2 we can see that the model's RMSFE declines more or less continuously over the prediction period, which means that new information has a monotonic and negative effect on uncertainty. In order to formally test the decline in uncertainty, as more data arrive we apply the test for forecast rationality proposed by Patton and Timmerman (2012). Table 4 reports the p-values of three monotonicity tests for, respectively, the forecast errors, the mean-squared forecast, and covariance between the forecast and the target variable (see the appendix for a description of the test). Monotonicity cannot be rejected by any of the three tests confirming the evidence of Figure 2 and proving the importance of incorporating new information as it arrives in the forecast update.

Table 3: Diebold-Mariano test of equal forecasting accuracy

	Forecast		Nowcast		Backcast	
	AR	BCB	AR	BCB	AR	BCB
1m	6.09	0.26	6.61	0.85	3.76	0.96
	(3.00)	(1.18)	(3.03)	(0.78)	(1.46)	(0.35)
2m	7.80	1.27	8.01	1.49	3.93	0.55
	(3.21)	(1.14)	(3.24)	(0.74)	(1.50)	(0.22)
3m	9.17	1.71	8.50	1.31		
	(3.34)	(1.17)	(3.31)	(0.52)		

Notes. The table reports the estimated constant and the HAC estimator of its standard error in the first, second, and third month of the forecast, nowcast, and backcast, respectively. The AR and BCB professional forecasts are compared against the nowcast model.

Table 4: Monotonicity Tests

	$\Delta^e \geq 0$	$\Delta^f \geq 0$	$\Delta^c \geq 0$
nowcast model	0.4963	0.4977	0.5024

Notes. The table reports the p-values of three monotonicity test for, respectively, the forecast errors, the mean-squared forecast, and covariance between the forecast and the target variable.

5.2 The News

The importance of calculating the news is twofold: first, given that the news is defined as the difference between the actual value of the data release and the value predicted by the model, it is possible to check whether the model is well specified in all of its dimensions. The average of the news for each release should be close to zero, and the standard deviation should be small ($|mean| < 2$ standard deviation). Table 5 confirms the previous statement. In addition, the table also compares the model's performance in predicting each of the series with that of the Bloomberg survey. We show that, for most series, the model's predictions are comparable to the Bloomberg survey predictions. Finally, we include in Table 5 the mean and standard deviation of the revisions for each of the series in the data set. As the means of the revisions are close to zero and the standard deviations are small, this suggests that the model's relative performance would have been similar in real time.[10]

Table 5: Average news and standard deviation

		Model		Bloomberg		Revisions	
	Units/ Transformation	Mean	StD	Mean	StD	Mean	StD
Merchandise exports	US$/MoM	-0.25	7.04	0.74	11.68	0.85	8.95
Merchandise imports	US$/MoM	0.89	6.27	0.39	10.31	0.43	8.53
PMI Manufacturing	D.I./Levels	-0.16	1.77	-0.07	0.22	0.01	0.13
Industrial production	Index/MoM	-0.10	1.92	0.38	1.09	-0.05	0.54
Manufacturing sales	Index/MoM	-0.15	2.39				
Capacity utilization	Percentage/Diff.	-0.01	0.37	-0.81	0.68	-0.80	0.46
Economic activity index	Index/MoM	-0.07	0.78				
Extended retail trade	Index/MoM	0.08	2.63	-0.10	2.00	-0.08	2.67
Retail trade: volume	Index/MoM	0.30	0.85	-0.05	0.85	-0.01	0.60
Registered jobs created	Thous. Units/YoY	-4,369.9	72,134.4	1,069	46,725	-	-
Formal employment	Index/Diff.	0.03	0.17				
Consumer confidence index	Index/Diff.	-0.24	3.34	-0.48	6.06	0.22	4.41
Monthly gross domestic product	Mil. Reais/MoM	-0.23	2.31				
Real gross domestic product	Index/MoM	0.14	0.59	0.04	0.45	-0.07	0.56

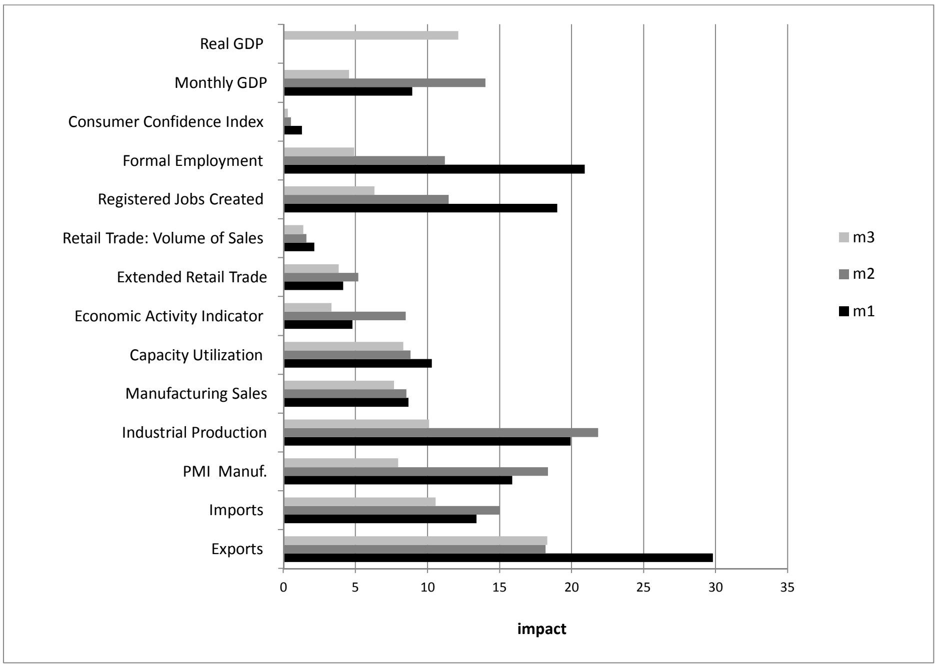
Notes. D.I.= diffusion index; Diff.= differences; Thous. Units = Thousand Units; Manuf. = Manufacturing; Mil. Reais = Million Reais.

The second important feature of the news within a nowcasting framework is that it allows interpretation of all the data releases in terms of the signals they give about current economic conditions (Bańbura and Modugno, 2010). The impact that a given release has on the GDP

[10]Note that the Bloomberg survey is conducted in real time, and the respondents whose forecasts it reflects are attempting to predict the first release of each series, whereas the reconstruction of the model's predictions is based on the last available vintage of data, ignoring revisions.

nowcast is the product of two variables: the news (or the unexpected component of the release value), and the relevance of the series in relation to GDP, which is expressed as its weight (i.e., impact = news x weight). Figure 3 shows the average impact of each variable in the first, second, and third month of the quarter. See appendix A.4 for the decomposition of the average impact.

Figure 3: Variables' relevance



Notes. Variables' average impact in the first (m1), second (m2), and third (m3) month of the nowcast.

6 Conclusions

The nowcasting model for Brazil, presented in this article, proves the relevance of updating GDP forecasts to take advantage of the flow of data releases.

Institutional forecasts, which in Brazil are revised as often as once a week, perform as well as model-based forecasts. This result is interesting because it suggests that judgmental forecasts are able to incorporate the information as efficiently as a linear time invariant model. This finding proves, on the one hand, that professional forecasters consider appropriate information to form their predictions. On the other hand, it proves that pure judgment (which can be translated in nonlinearities, time variations, and soft information) turns out to be no more accurate to the scope of forecasting.

The nowcasting model is also a useful instrument to stress the single variable's relevance to the updating process. In Brazil, trade variables (in particular exports), given their timeliness, turn out to have a huge impact on the forecasting revisions. Industrial production, manufacturing PMI and employment variables are also relevant.

Appendix

A1. Selecting the Number of Factors and Lags

We select the optimal number of factors using an information criteria approach. The idea is to choose the number of factors that maximizes the general fit of the model using a penalty function to account for the loss in parsimony. Bai and Ng (2002) derive information criteria to determine the number of factors in approximate factor models when the factors are estimated by principal components. They also show that their information criterion (IC) can be applied to any consistent estimator of the factors provided that the penalty function is derived from the correct convergence rate.

Table A.1 reports the information criterion and the sum of the variance of the idiosyncratic components for the different specifications, which allow for a different number of factors. The

Table A1: Model selection (number of factors)

	Sample 1		Sample 2		Sample 3	
	IC	V	IC	V	IC	V
1	-0.03	0.67	-0.01	0.71	-0.04	0.69
2	-0.02	0.47	0.07	0.55	0.08	0.56
3	0.32	0.46	0.26	0.48	0.18	0.44
4	0.23	0.30	0.41	0.40	0.17	0.31
T	11		47		128	
N	14		12		14	

Notes. IC stands for Information Criteria, V is the sum of the variance of the idiosyncratic component.

IC selects the model with one factor. Given that our data set is strongly unbalanced at the top, and some series are more recent than others, we report the test on three different samples. The first (sample 1) considers a balanced panel in the estimation period 1995:Q1 to 2006:Q4 (14 series and 11 observations), the second (sample 2) a restricted balanced panel where we exclude two of the most recent series (12 series 47 observations), the third (sample 3) is a balanced panel that incorporates the whole sample (estimation and forecasting period). The choice of one factor is confirmed across the different samples.

In order to select the number of lags in Equation 4 of the model, we report in Table A.2 the results on the Akaike information criterion, which selects two lags.

Table A2: Model selection (number of lags)

Number of lags	Akaike information criteria
1	0.96
2	0.74
3	0.79
4	0.79

Notes. The lag is chosen in correspondence with the minimum AIC value.

A2. Diebold-Mariano Test

Denote the loss associated with forecast error e_t by $L(e_t)$ and the time-t loss differential between forecasts 1 and 2 as $d_{12t} = L(e_{1t}) - L(e_{2t})$. The Diebold-Mariano (DM) requires only that the loss differential is covariance stationary:

$$\begin{aligned} E(d_{12t}) &= \mu, \forall t \\ cov(d_{12t}, d_{12t-\tau}) &= \gamma(\tau), \forall t \\ 0 < var(d_{12t}) &= \sigma_2 < \infty \end{aligned}$$

The key hypothesis of equal predictive accuracy (i.e., equal expected loss) corresponds to $E(d_{12t}) = 0$, in which case, under the maintained assumption DM:

$$DM_{12} = \frac{\bar{d}_{12}}{\hat{\sigma}_{\bar{d}_{12}}} \xrightarrow{d} N(0,1),$$

where $\bar{d}_{12} = \frac{1}{T}\sum_{t=1}^{T} d_{12t}$ is the sample mean loss differential and $\sigma_{\bar{d}_{12}}$ is a consistent estimator of the standard deviation of $\bar{d}_{12}$.

DM is thus an asymptotic $z - test$ of the hypothesis that the mean of a constructed but observed series (the loss differential) is zero. Forecast errors, and hence loss differential, though, may be serially correlated for various reasons. In this paper, we calculate the DM statistics by regression of the loss differential on an intercept, using heteroskedasticity and autocorrelation robust (HAC) standard errors. In a fully articulated econometric model in which we have pseudo out-of-sample forecasts, following West (1996), we define the test on the sample mean quadratic loss as follows:

$$\bar{d}_{12} = \frac{\sum_{t=t^*+1}^{T}(e^2_{1,t|t-1} - e^2_{2,t|t-1})}{T - t^*},$$

where $e_{t|t-1}$ is a time-t pseudo out-of-sample one-step ahead forecast error. We do not consider a rolling scheme, so results should be taken with caution, as the test ignores estimation uncertainty.

A3. Monotonicity Test

We rely on the first three tests of Patton and Timmermann (2012), and we report the p-values for the nowcast model.

Test 1: Monotonicity of the forecast errors

Let us define $\tilde{y}_t = y^k_{t,1}$ and $e_{t|\Omega_v} = \tilde{y}_t - E[\tilde{y}_t|\Omega_v]$ as the forecast error obtained on the basis of the information set corresponding to the data vintage Ω_v and by $e_{t|\Omega_{v+1}}$ that obtained on the basis of a larger more recent vintage $v + 1$ and $v = 1, ..., V$.

The mean squared Error (MSE) differential is $\Delta^e_v = E[e^2_{t|\Omega_v}] - E[e^2_{t|\Omega_{v+1}}]$.

The test is: H0 : $\Delta^e \geq 0$ vs H1 :$\Delta^e \ngeq 0$, where the $(V - 1) \times 1$ vector of MSE-differentials is given by $\Delta^e \equiv (\Delta^e_1, ..., \Delta^e_{V-1})'$.

Test 2: Monotonicity of the mean squared forecast

Define the mean squared forecast (MSF) for a given vintage as $E[\tilde{y}^2_{t|\Omega_v}] = E[E[\tilde{y}^2_t|\Omega_v]]$ and consider the difference $\Delta^f_v = E[\tilde{y}^2_{t|\Omega_v}] - E[\tilde{y}^2_{t|\Omega_{v+1}}]$ and its associated vector Δ^f.

The test is H0 : $\Delta^f \leq 0$ vs H1 : $\Delta^f \nleq 0$.

Test 3: Monotonicity of covariance between the forecast and the target variable

Here we consider the covariance between the forecast and the target variable for different vintages v and the difference $\Delta_v^c = E[\tilde{y}_{t|\Omega_v}\tilde{y}_t] - E[\tilde{y}_{t|\Omega_{v+1}}\tilde{y}_t]$. The associated vector is defined as Δ^c and the test is H0 : $\Delta^c \leq 0$ vs H1 : $\Delta^c \nleq 0$.

A4. Impact of the Releases on the Nowcast

Table A3: Impact of the Releases on the Now-cast

	A			B			C		
	m1	m2	m3	m1	m2	m3	m1	m2	m3
Merchandise exports	3.764	3.360	2.365	7.921	5.419	7.741	29.819	18.209	18.308
Merchandise imports	2.555	2.284	1.623	5.243	6.581	6.511	13.396	15.029	10.571
PMI manufacturing	11.500	9.030	4.210	1.382	2.033	1.889	15.893	18.359	7.952
Industrial production	9.797	9.290	8.115	2.035	2.353	1.245	19.940	21.859	10.103
Manufacturing sales	3.806	3.609	3.156	2.277	2.362	2.429	8.664	8.523	7.665
Capacity utilization	25.875	25.075	21.539	0.398	0.351	0.386	10.305	8.814	8.307
Economic activity indicator	8.210	7.712	6.102	0.582	1.101	0.548	4.778	8.492	3.341
Extended retail trade	1.913	1.809	1.393	2.162	2.864	2.749	4.136	5.180	3.829
Retail trade: volume of sales	2.205	2.048	1.678	0.973	0.775	0.811	2.146	1.587	1.361
Registered jobs created	0.000	0.000	0.000	84,996.848	65,143.536	67,609.663	19.012	11.478	6.313
Formal employment	92.400	80.040	36.965	0.226	0.140	0.133	20.911	11.209	4.911
Consumer confidence index	0.302	0.198	0.099	4.241	2.566	3.086	1.282	0.507	0.305
Monthly GDP	5.080	4.430	2.742	1.760	3.168	1.658	8.942	14.032	4.545
Real GDP			20.522			0.592			12.145

Notes. A is the average weight; B is the news standard deviation; C is the average impact equal to $A \cdot B$.