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Applying a Microfounded-Forecasting Approach to Predict Brazilian Inflation*

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Abstract

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

In this paper, we investigate whether combining forecasts from surveys of expectations is a helpful strategy for forecasting inflation in Brazil. We employ the FGV-IBRE Economic Tendency Survey, which consists of monthly qualitative information from approximately 2,000 consumers since 2006, and also the Focus Survey of the Central Bank of Brazil, with daily forecasts since 1999 from roughly 250 professional forecasters. Natural candidates to win a forecast competition in the literature of surveys of expectations are the (consensus) cross-sectional average forecasts (AF). In an exploratory investigation, we first show that these forecasts are a bias ridden version of the conditional expectation of inflation. The no-bias tests are conducted for the intercept and slope using the methods in Issler and Lima (2009) and Gaglianone and Issler (2015). The bias results reveal interesting data features: consumers systematically overpredict inflation (by 2.01 p.p., on average), whereas market agents underpredict it (by -0.68 p.p. over the same sample). Next, we employ a pseudo out-of-sample analysis to evaluate different forecasting methods: the AR(1) model, the Granger and Ramanathan (1984) forecast combination (GR), the consensus forecast (AF), the Bias-Corrected Average Forecast

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(BCAF), and the extended BCAF. Results reveal that: (i) the MSE of the AR(1) model is higher compared to the GR (and usually lower compared to the AF); and (ii) the extended BCAF is more accurate than the BCAF, which, in turn, dominates the AF. This validates the view that the bias corrections are a useful device for forecasting using surveys.

Keywords: Consensus Forecasts, Forecast Combination, Common Features, Panel Data.

JEL codes: C14, C33, E37.

1 Introduction

From a theoretical and empirical point-of-view, Bates and Granger (1969) made the econometric profession aware of the benefits of forecast combination. Their empirical results were later confirmed by a variety of time-series studies – e.g., Granger and Ramanathan (1984), Palm and Zellner (1992), Stock and Watson (2002a,b, 2006), Timmermann (2006), and Genre et al. (2013) – where the simple average of forecasts is shown to perform relatively well.

In a pioneering study on forecasting using panel-data techniques, Davies and Lahiri (1995) proposed testing forecast rationality using information across forecasts and forecast horizons employing a three-way decomposition¹. This led to a subsequent literature on what could be labelled *a panel-data approach to forecasting*; see Baltagi (2013) for a broader discussion on this topic. Some of these studies focused on forecast combination, e.g., Issler and Lima (2009), Gaglianone et al. (2011), Gaglianone and Lima (2012, 2014), Gaglianone and Issler (2015), and Lahiri, Peng, and Sheng (2015).

In Issler and Lima and Gaglianone and Issler, the main idea is that the *consensus forecast* (the cross-sectional average of individual forecasts) is a bias ridden version of the conditional expectation, which is the optimal forecast under a mean-squared-error (MSE) *risk function*. Once these potential biases are properly removed, one can construct forecasting devices that are optimal in the limit, i.e., that can approach the conditional expectation asymptotically.

In this paper we show empirically that combining forecasts in surveys is a promising empirical strategy to increase forecast accuracy. Our focus is on Brazilian inflation, a key variable on the *Inflation Targeting Regime*, implemented by the Central Bank of Brazil (BCB). In Brazil, there are two main surveys of expectations regarding inflation. The first is the *Focus Survey* – a survey of professional forecasters – kept by the BCB. The second is the *FGV-IBRE Economic Tendency Survey* – a survey of individual consumers. Both include forecasts for the official index used in the Inflation Targeting Regime – the IPCA, a Broad Consumer Price Index (CPI).

¹Prior to that, Palm and Zellner (1992) also employ a two-way decomposition to discuss forecast combination in a Bayesian and a non-Bayesian setup. But, the main focus of their paper is not on panel-data techniques, but on the usefulness of a Bayesian approach to forecasting.

Using information in these surveys, we employ the techniques in Issler and Lima and in Gaglianone and Issler to construct potentially optimal forecasts under MSE risk. The method discussed in the former shows that the mean of the consensus forecast is biased. The method discussed in the latter is *microfounded* and shows that the optimal forecast decision faced by an individual agent is related to the conditional expectation by an *affine* structure. This leads to the fact that the consensus forecast has two sources of bias – an intercept bias and a slope bias. Fortunately, they can be estimated to filter out the conditional expectation from a database of survey responses.

Using bias correction for the consensus forecast is a relevant empirical issue, since there is a growing forecasting literature in macroeconomics where the consensus forecast is used with no correction and rationality tests employing it usually find a result opposite to rationality; see, e.g., Coibion and Gorodnichenko (2012). Below, we show some evidence of these phenomena, and discuss some important implications regarding rationality tests.

The usefulness of survey data for forecasting has been recently shown in a variety of studies. For example, Ang et al. (2007) find that true out-of-sample survey forecasts (e.g. Michigan; Livingston) outperform a large number of out-of-sample single-equation and multivariate time-series competitors. Faust and Wright (2013) argue that subjective forecasts of inflation based on surveys seem to outperform model-based forecasts in certain dimensions, often by a wide margin. In a world where there is an increasing availability of reliable survey data provided electronically, it is interesting to examine how one could efficiently use it. This is exactly the objective of this paper, where we exploit the fact that the Focus Survey has information on more than 250 professional forecasters and that the Economic Tendency Survey keeps responses of about 1,500 respondents on inflation expectations in every month.

The rest of the paper is divided as follows. Section 2 discusses the econometric techniques employed in this paper, with some focus on the work of Issler and Lima (2009) and of Gaglianone and Issler (2015), but covering the adjacent literature as well. Section 3 presents a real-time forecasting exercise with data from the FGV survey of consumer expectations on inflation and from the Focus survey of the BCB

on inflation expectations of professional forecasters. It also discusses rationality tests using the consensus forecasts and its possible shortcomings. Section 4 concludes.

2 Econometric Methodology

Forecast combination has proved to be a valuable tool at least since Bates and Granger (1969). Palm and Zellner (1992) and Davies and Lahiri (1995) pioneered the use of panel-data techniques in forecasting. This section discusses in some detail the forecast-combination approach put forth by Gaglianone and Issler (2015) on how to combine survey expectations to obtain optimal forecasts in a panel-data context. Some parts of the material therein can also be found in Issler and Lima (2009) and in Lahiri, Peng and Sheng (2015).

The techniques discussed in this section are appropriate for forecasting a weakly stationary and ergodic univariate process $\{y_t\}$ using a large number of forecasts, coming from forecast surveys (expectations) on the variable in question – y_t . Some (or all) of these responses can be generated by using econometric models, but then we have no knowledge of them. We label individual forecasts of y_t , computed using information sets lagged h periods, by $f_{i,t}^h$, $i = 1, 2, \dots, N$, $h = 1, 2, \dots, H$, and $t = 1, 2, \dots, T$. Therefore, $f_{i,t}^h$ are h -step-ahead forecasts of y_t , formed at period $t-h$, and N is the number of respondents of this opinion poll regarding y_t . Gaglianone and Issler show that, in a variety of interesting cases, optimal forecasts are related to $\mathbb{E}_{t-h}(y_t)$ – the conditional expectation of y_t , computed using information lagged h periods – by an affine function:

$$f_{i,t}^h = k_i^h + \beta_i^h \mathbb{E}_{t-h}(y_t) + \varepsilon_{i,t}^h. \quad (1)$$

This result is somewhat expected given the pioneering work of Granger (1969). He shows that, under a mean-squared-error (MSE) *risk function* and proper regularity conditions, the optimal forecast is equal to $\mathbb{E}_{t-h}(y_t)$. Moreover, if the risk function is asymmetric and proper regularity conditions are met, then Granger showed that the optimal forecast is equal to $\mathbb{E}_{t-h}(y_t) + k_i^h$; see also the later developments in Christoffersen and Diebold (1997), Elliott and Timmermann (2004), Patton and

Timmermann (2007), and Elliott, Komunjer, and Timmermann (2008), for example.

Gaglianone and Issler consider a setup with two layers of decision making. In the first layer, individuals (survey respondents) form their *optimal* point forecasts ($f_{i,t}^h$) of a random variable y_t by using a specific *loss function*. They allow for the existence of asymmetry of the loss function and different assumptions about knowledge of the DGP of y_t . The optimal forecasts $f_{i,t}^h$ will be available as survey results, where the number of respondents is potentially large, i.e., $N \rightarrow \infty$, and these surveys can be periodically taken on a large number of different occasions, i.e., $T \rightarrow \infty$. In the second layer of decision-making, an econometrician will be the final user of this large number of forecasts, operating under an MSE *risk function*. Her/his challenge is to uncover $\mathbb{E}_{t-h}(y_t)$ – the optimal forecast of the second layer of decision making.

Gaglianone and Issler employ the basic assumptions in the econometric forecast literature to derive a consistent estimate of $\mathbb{E}_{t-h}(y_t)$, which can be obtained by using Hansen’s (1982) generalized method of moments (GMM). Start by taking a cross-sectional average of (1), after using:

$$y_t = \mathbb{E}_{t-h}(y_t) - \eta_t^h, \quad (2)$$

noting that η_t^h is a martingale-difference sequence by construction, i.e., $\mathbb{E}_{t-h}(\eta_t^h) = 0$. Under suitable assumptions, they show that the following system of equations can be used to estimate the key parameters \bar{k}^h and $\bar{\beta}^h$ in:

$$\mathbb{E} \left[\left(\overline{f_{\cdot,t}^h} - \bar{k}^h - \bar{\beta}^h y_t \right) \otimes z_{t-s} \right] = 0, \quad h = 1, 2, \dots, H, \quad (3)$$

where z_{t-s} is a vector of instruments, dated $t-s$ or older, $s \geq h$, $\overline{f_{\cdot,t}^h} = \frac{1}{N} \sum_{i=1}^N f_{i,t}^h$, $\bar{k}^h = \frac{1}{N} \sum_{i=1}^N k_i^h$ and $\bar{\beta}^h = \frac{1}{N} \sum_{i=1}^N \beta_i^h$, for each h . Over-identification requires that $\dim(z_{t-s}) > 2$.

Gaglianone and Issler argue that there is no need to estimate individual coefficients k_i^h and β_i^h – only their means to be able to identify and estimate $\mathbb{E}_{t-h}(y_t)$. In doing so, they avoid the curse of dimensionality given that $N \rightarrow \infty$. As long as these cross-sectional averages converge, GMM using time-series restrictions delivers

consistent estimates of the respective parameter means.

Current surveys, however, usually approximate better the case where $T \rightarrow \infty$, while N is small or diverges at a smaller rate than T . Under additional conditions on the cross-sectional averages $\overline{f_{\cdot,t}^h} = \frac{1}{N} \sum_{i=1}^N f_{i,t}^h$, $\overline{k^h} = \frac{1}{N} \sum_{i=1}^N k_i^h$ and $\overline{\beta^h} = \frac{1}{N} \sum_{i=1}^N \beta_i^h$, Gaglianone and Issler show that one can still estimate $\mathbb{E}_{t-h}(y_t)$ consistently, when $T \rightarrow \infty$ first, and then $N \rightarrow \infty$.

One way to exploit all possible moment conditions implicit in (3) is to stack all the restrictions across h (finite) as:

$$\mathbb{E} \left[\begin{pmatrix} \overline{f_{\cdot,t}^1} - \overline{k^1} - \overline{\beta^1} y_t \\ \overline{f_{\cdot,t}^2} - \overline{k^2} - \overline{\beta^2} y_t \\ \vdots \\ \overline{f_{\cdot,t}^H} - \overline{k^H} - \overline{\beta^H} y_t \end{pmatrix} \otimes z_{t-s} \right] = 0, \quad (4)$$

where the problem collapses to one where we have $H \times \dim(z_{t-s})$ restrictions and $2H$ parameters to estimate. As before, over-identification requires that $\dim(z_{t-s}) > 2$. Given a choice of H , GMM estimation of (4) is efficient. A less efficient alternative to estimate the whole stacked system (4) is to estimate separately (3) for every horizon h , which could also be attempted for computational reasons.

Using GMM estimates, $\widehat{\overline{k^h}}$ and $\widehat{\overline{\beta^h}}$, obtained when $T \rightarrow \infty$, Gaglianone and Issler show the critical result that:

$$\frac{1}{N} \sum_{i=1}^N \frac{f_{i,t}^h - \widehat{\overline{k^h}}}{\widehat{\overline{\beta^h}}} \xrightarrow{p} \mathbb{E}_{t-h}(y_t), \quad (5)$$

in a variety of different setups: when $T \rightarrow \infty$ first, and then $N \rightarrow \infty$; when $N \rightarrow \infty$ first, and then $T \rightarrow \infty$; and when $N, T \rightarrow \infty$ in a joint limit framework, all using the method in Phillips and Moon (2009). The conditions under which (5) holds vary according to the asymptotic setup.

Equation (5) offers a way to filter the consensus forecast $\frac{1}{N} \sum_{i=1}^N f_{i,t}^h$ extracting $\mathbb{E}_{t-h}(y_t)$ in the limit. Thus, it delivers an estimate of the optimal forecast in the second layer of decision making. It can be viewed immediately as a forecast-combination method.

In a truly out-of-sample forecasting exercise involving surveys, there are usually 3 consecutive distinct time sub-periods, where time is indexed by $t = 1, 2, \dots, T_1, \dots, T_2, \dots, T$. The first sub-period E is labeled the “estimation sample,” where models are usually fitted to forecast y_t in the subsequent period, if that is the case. The number of observations in it is $E = T_1 = \kappa_1 \cdot T$, comprising $(t = 1, 2, \dots, T_1)$. For the other two, we follow the standard notation in West (1996). The sub-period R (for regression) is labeled the post-model-estimation or “training sample”, where realizations of y_t are usually confronted with forecasts produced in the estimation sample, and weights and bias-correction terms are estimated, if that is the case. It has $R = T_2 - T_1 = \kappa_2 \cdot T$ observations in it, comprising $(t = T_1 + 1, \dots, T_2)$. The final sub-period is P (for prediction), where genuine out-of-sample forecast is entertained. It has $P = T - T_2 = \kappa_3 \cdot T$ observations in it, comprising $(t = T_2 + 1, \dots, T)$. Notice that $0 < \kappa_1, \kappa_2, \kappa_3 < 1$, $\kappa_1 + \kappa_2 + \kappa_3 = 1$, and that the number of observations in these three sub-periods keep a fixed proportion with T – respectively, κ_1 , κ_2 and κ_3 – being all $O(T)$.

It is worth mentioning that the method proposed by Gaglianone and Issler extends the previous literature of forecasting within a panel-data framework, e.g., Palm and Zellner (1992), Davies and Lahiri (1995), Issler and Lima (2009) and Lahiri, Peng, and Sheng (2015).

For example, their setup encompasses that of Davies and Lahiri (1995), reproduced below with our notation:

$$y_t - f_{i,t}^h = - (k_i^h + \eta_t^h + \varepsilon_{i,t}^h), \quad (6)$$

who imposed $\beta_i^h = 1$ for all $i = 1, \dots, N$ and all $h = 1, \dots, H$. Also, it generalizes the results in Issler and Lima, where slopes are restricted as $\beta_i^h = 1$ for all $i = 1, \dots, N$. Here, we have two sources of bias correction: intercept and slope. Notice that both arise from a structural affine function that links individual forecasts to the conditional expectation. In itself, this provides a general framework that can be used whenever a panel of forecasts is available.

The method proposed by Gaglianone and Issler is appropriate to cover any type of survey where potentially the number of observations T is large, encompassing the

cases where the number of survey respondents and of time observations is large – *big data*, and also the case where the number of time observations is large but the number of respondents is fixed – standard continuous macroeconomic surveys.

The way Gaglianone and Issler identify the conditional expectation can be viewed as a combination of cross-sectional averages with standard GMM moment restrictions, where the affine structure offers natural orthogonality restrictions allowing the estimation of bias-correction terms. They circumvent the *curse of dimensionality* that arises from the factor structure (large N) by employing these cross-sectional averages.

3 Empirical Application

3.1 Data

FGV's Consumer Survey

The FGV-IBRE Economic Tendency Survey compiles business and consumers expectations of key economic series in Brazil. The Brazilian Institute of Economics (IBRE) is a pioneer in surveys, and this one runs since 1966. Since September, 2005, FGV-IBRE conducts a monthly consumer survey, which consists of qualitative information on household consumption, savings, financial variables, employment, etc. The survey has a country-wide coverage (seven major state capitals) with approximately 2,000 consumers. Survey respondents are classified into four classes of household monthly income as follows²: *Income Level 1 - Up to R\$ 2,100; Income Level 2 - Between R\$ 2,100.01 and R\$ 4,800.00; Income Level 3 - Between R\$ 4,800.01 and R\$ 9,600.00; Income Level 4 - More than R\$ 9,600.01*. Survey information can also be broken down by different classes of education: *Group 1 – No education or incomplete first year; Group 2 – Complete first year or incomplete primary education; Group 3 – Complete primary education or incomplete secondary education; Group 4 – Complete secondary education or incomplete undergraduate; Group 5 – Complete undergraduate; and Group 6 – Graduate studies*.

²See Consumer Survey: Methodological Features (April 2013), available at <http://portallibre.fgv.br>

The panel is unbalanced and on average each household is interviewed 7.81 times (months) per year. We possess micro data at the individual level for this survey, beginning in January 2006 through to May 2015 ($T = 113$ months). Overall, our sample has $N \times T = 164,479$ responses. Decomposing our sample into N and T , gives the following breakdown: $T = 113$ months, and an average of approximately $N = 1,456$ individuals per month. The key question of interest for us is the following: *"In your opinion, how much will be Brazilian inflation over the next 12 months?"* We excluded outliers in the data set whenever the respondent answered that inflation would be greater than 100% in the next 12 months. In our sample, it was rare to observe 12-month inflation greater than 10%, so we considered this type of response completely out of scope³.

Focus Survey of the Central Bank of Brazil

The *Focus Survey* of forecasts of the Central Bank of Brazil (BCB) contains daily (working days) forecasts from roughly 250 registered institutions since 1999, the year when Brazil implemented its *Inflation-Targeting Regime*⁴. About 100 of these institutions are actively feeding the data base with forecasts on any given day. Institutions include professional forecasters – commercial banks, asset management firms, consulting firms, non-financial firms or institutions, academics, etc. Participants can provide forecasts for a large number of economic variables, e.g., inflation using different price indices, interest and exchange rates, GDP, industrial production, balance of payments accounts, fiscal variables, etc. and for different forecast horizons, e.g., current month, next month, current year, 5 years from now etc.

Our focus here is on Brazilian inflation, measured by the Brazilian Consumer Price Index – IPCA, which is the official inflation target of the Brazilian *Inflation-Targeting Regime*. Our sample covers daily inflation forecasts collected from January 2nd, 2004 until May, 28th, 2015 (2,861 workdays)⁵. In each day t , $t = 1, \dots, T$, survey

³With this criterium we excluded 349 observations of a total of 164,479.

⁴The *Focus survey* is widely used in the Brazilian economy and its excellence has been internationally recognized. In 2010, the survey received the Certificate of Innovation Statistics, due to a second place in the II Regional Award for Innovation in Statistics in Latin America and Caribbean, offered by the World Bank.

⁵Since the survey had a small cross-sectional coverage (small N) in its first years, we only considered *post-2003* data.

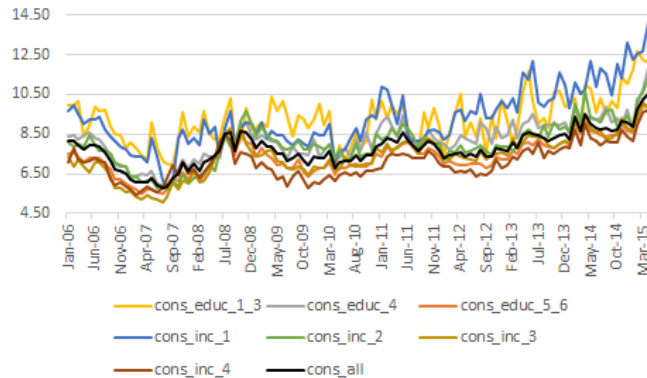
respondent i , $i = 1, \dots, N$, may inform her/his expectations regarding inflation rates all the way up to the next 18 months, as well as for the next twelve months and for the next 5 years on a year-end basis. The data set regarding the twelve-month-ahead inflation forecasts forms an unbalanced panel ($N \times T$) containing an amount of 244,043 observations. Decomposing our total number of observations into N and T , gives the following breakdown: $T = 2,861$ daily observations, and an average of $N = 85.3$ forecasters in our sample. For more information on this data set, see Carvalho and Minella (2012) and Marques (2013).

Despite the fact that the Focus Survey has a longer time span and a higher frequency than FGV's Consumer Survey (working day vs. monthly), our sample size is, most of the time, constrained by the span and frequency of the latter.

Consensus Forecasts

Our target variable y_t – is Brazilian inflation – as measured by the Broad Consumer Price Index (IPCA), collected at the monthly frequency. The consumer forecasts $f_{i,t}^h$ from the FGV survey regarding expected inflation rate over the next 12 months ($h = 12$ months) are cross-sectionally averaged, forming the so-called "consensus" forecasts $\overline{f_{\cdot,t}^h} = \frac{1}{N} \sum_{i=1}^N f_{i,t}^h$. Besides the average over the entire data set (approximately 1,500 households), labelled hereafter as "cons_all", the individual forecasts are also averaged by selected demographic groups, according to the education level of the survey participant or to its level of income. The breakdown by education yields the following consensuses: cons_educ_1_3; cons_educ_4 and cons_educ_5_6; respectively educational levels groups 1 through 3, level 4, and group level 5 through 6. For income, we breakdown the groups numbered from 1 to 4, respectively: cons_inc_1; cons_inc_2; cons_inc_3; cons_inc_4. Figure 1 plots these eight time series of aggregate (cross-sectional mean) forecasts.

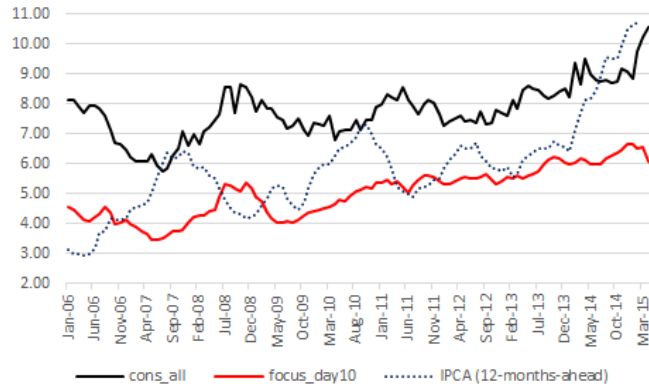
Figure 1 - Consensus inflation forecasts $\overline{f_{.,t}^h}$
from the FGV consumer survey (% 12-months-ahead)



There is considerable heterogeneity across groups, either from an education or income point of view. Low income households usually forecast higher inflation rates *vis-à-vis* the forecasts of higher-income families. Obviously, inflation is not perceived equally by all families, each with its own consumption bundle. Poorer households spend more on food, while higher-income households spend a larger proportion of their budget on housing, education, and leisure. By construction, the IPCA index follows closely the cost-of-living of households with income well above the income level of our categories 1 and 2.

Figure 2 compares the consensuses of consumer forecasts (`cons_all`), professional (or market forecasts from the *Focus Survey*), and the twelve-month-ahead IPCA inflation rate. The latter is exactly what these forecasts are supposed to track. Market forecasts are collected at the 10th and 15th days of each month (`focus_day10`, `focus_day15`). This makes the Focus consensus consistent with the days in which the data is collected for the FGV consumer survey. On average, the consumer consensus has a positive bias, while the consensus of professional forecasters has a negative bias. It is also worth noting that the behavior of both consensuses is very different at the end of the sample period. While the consumer consensus follows the observed increase in inflation, the consensus of professional forecasters gets it completely wrong, predicting a decrease in inflation.

Figure 2 - Comparison of the consumer and market inflation forecasts $\overline{f_{\cdot,t}^h}$ with the actual inflation rate y_t (% 12 months)



3.2 Empirical Results

Descriptive statistics

Table 1 shows the pairwise sample correlations of the consensus forecasts. Notice that all series are highly correlated. The consensus forecasts of consumers and of market agents show a sample correlation of 0.80.

Table 1 - Sample Correlations

Variable	cons_all	cons_ed13	cons_ed4	cons_ed56	cons_inc1	cons_inc2	cons_inc3	cons_inc4	focus_d10	focus_d15
cons_all	1.000									
cons_ed13	0.768	1.000								
cons_ed4	0.950	0.694	1.000							
cons_ed56	0.986	0.702	0.904	1.000						
cons_inc1	0.874	0.808	0.900	0.822	1.000					
cons_inc2	0.945	0.708	0.911	0.930	0.785	1.000				
cons_inc3	0.957	0.667	0.909	0.965	0.802	0.892	1.000			
cons_inc4	0.927	0.662	0.832	0.950	0.785	0.812	0.890	1.000		
focus_d10	0.803	0.543	0.808	0.816	0.779	0.771	0.867	0.753	1.000	
focus_d15	0.803	0.542	0.806	0.819	0.776	0.768	0.869	0.758	0.999	1.000

Note: Full sample: January 2006 to May 2015 (T=113 observations).

Table 2 presents the sample mean and the respective estimation of the asymptotic standard error based on the number of sample observations $T = 113$. Next, we investigate whether or not the consensus forecasts Granger Cause future inflation using Sims' test. More than half of the consensus forecasts for consumers Granger Cause future inflation, i.e., are leading indicators of future inflation. This is also true for the consensus including all consumers. The same is true for both the consensus of professional forecasters. Therefore, they will be useful as tools in forecasting future inflation.

Table 2 - Mean Forecast, Standard Error, and
Granger Causality Test

Variable	Mean	Std. Error	GC test
cons_all	7.78	0.09	0.0296 **
cons_educ_1_3	9.21	0.11	0.5110
cons_educ_4	8.23	0.10	0.0219 **
cons_educ_5_6	7.38	0.09	0.0423 **
cons_inc_1	9.32	0.15	0.0175 **
cons_inc_2	8.01	0.10	0.1171
cons_inc_3	7.41	0.10	0.1257
cons_inc_4	7.10	0.08	0.2206
focus_day10	5.05	0.08	0.0306 **
focus_day15	5.06	0.08	0.0211 **

Notes: Full sample: January 2006 to May 2015 (T=113 observations).

Confidence Interval based on asymptotic values: std. error = sample std.dev./ \sqrt{T} .

The last column shows the p-values of the Granger Causality test (12 lags) based on the null hypothesis: Forecast does not GC IPCA. ** denotes rejection at a 5% significance level.

Bias-correction devices

In Figure 2, we provided soft evidence that the consensus forecasts are biased as predictors of future inflation. Next, we formally test for zero bias employing the Bias-Corrected Average Forecast (BCAF) approach of Issler and Lima (2009). There, the estimate of the out-of-sample additive forecast bias $\overline{k^h}$ is:

$$\widehat{k^h} = \frac{1}{NR} \sum_{t=T_1+1}^{T_2} \sum_{i=1}^N (y_t - f_{i,t}^h), \quad (7)$$

where its robust standard error is computed taking into account possible spatial and time-dependence. Here, we employ the whole sample in estimating $\overline{k^h}$: $t = 1, 2, \dots, T$, where the consensus data runs from January 2006 to July 2014, whereas the IPCA sample runs from December 2006 to June 2015.

Results of the zero-bias test are presented in Table 3. As expected from the

plot in Figure 2, all consumer forecasts showed a negative bias, i.e., consumers overpredicted future inflation, while all professional forecasts underpredicted future inflation. The formal evidence provided below calls for the use of bias-correction devices in constructing optimal forecasts.

Table 3 - BCAF additive bias $\overline{k^h}$ test (Issler and Lima, 2009)

Variable	Mean	Bias	Robust S.E.	Zero-bias test (p-value)
cons_all	7.62	-2.01	0.26	0.000
cons_educ_1_3	9.01	-3.41	0.27	0.000
cons_educ_4	8.06	-2.45	0.26	0.000
cons_educ_5_6	7.21	-1.61	0.26	0.000
cons_inc_1	9.02	-3.41	0.26	0.000
cons_inc_2	7.83	-2.22	0.28	0.000
cons_inc_3	7.24	-1.64	0.26	0.000
cons_inc_4	6.93	-1.33	0.25	0.000
focus_day10	4.92	0.68	0.21	0.001
focus_day15	4.93	0.68	0.21	0.001

Notes: Forecasts' sample: January 2006 to July 2014. IPCA sample: December 2006 to June 2015

(103 observations). Average IPCA (in 12 months) = 5.61%. Unconditional (additive) bias is defined as:

IPCA - mean(forecast). The zero-bias test is based on the null hypothesis $H_0: \overline{k^h} = 0$.

Robust std. error employs Newey-West. See Issler and Lima (2009).

A possible shortcoming of the test in Table 3 is that it is implicitly assumed that $\overline{\beta^h} = 1$. However, Gaglianone and Issler (2015) showed that, in general, there is a intercept and a slope bias term for the consensus forecast, suggesting the use of the Extended BCAF setup, where the parameters $\overline{k^h}$ and $\overline{\beta^h}$ are estimated by the generalized method of moments (GMM) based on y_t and $f_{i,t}^h$ ⁶.

Results of GMM estimation and of the no-bias test are presented in Table 4. We use a set of instruments z_{t-s} containing two lags of of the consensus forecasts $\overline{f_{.,t}^h}$, up to four lags of the output gap⁷ and two lags of the Commodity Price Index (IC-Br),

⁶The "iterative" procedure of Hansen et al. (1996) is employed in the GMM estimation and the initial weight matrix is the identity.

⁷The Hodrick-Prescott filtered output gap is defined as the difference between the log real monthly GDP (IBRE/FGV).

which weighting structure is designed to measure the impact of commodity prices on Brazilian consumer inflation⁸; see the Appendix for results using an alternative set of instruments. Hansen’s Over-Identifying Restriction (OIR) test is employed in order to check the validity of GMM estimates. At the usual significance levels, we do not observe any rejection for the OIR test. The no-bias test consists of a joint test of the null hypothesis $H_0 : [\overline{k^h} = 0; \overline{\beta^h} = 1]$, which can be regarded as a modified Mincer-Zarnowitz test. We reject the null of no-bias on all occasions, showing that the consensus forecasts are a bias ridden version of the conditional expectation $\mathbb{E}_{t-h}(y_t)$.

From equation (5), note that, under the null $H_0 : [\overline{k^h} = 0; \overline{\beta^h} = 1]$, the aggregate forecast $\overline{f_{.,t}^h}$ should converge in probability to the conditional expectation $\mathbb{E}_{t-h}(y_t)$, with no need for bias correction. However, if the null is rejected, we should expect a corrected version of the consensus forecast to produce superior forecasts *vis-à-vis* the consensus forecasts. These are exactly our findings below.

⁸The adopted set of instruments is slightly modified for the lower education groups (cons_educ_1_3) and the market forecasts (focus_day10; focus_day15).

Table 4 - Extended BCAF estimation and No Bias Test

Parameters	$\widehat{k^h}$	Robust	t-stat	$\widehat{\beta^h}$	Robust	t-stat	OIR test	No Bias test
Consensus		S.E.	p-value		S.E.	p-value	p-value	p-value
cons_all	-0.11	2.59	0.97	1.34	0.46	0.00	0.115	0.000
cons_educ_1_3	2.77	3.40	0.41	1.08	0.59	0.07	0.207	0.000
cons_educ_4	0.65	2.12	0.76	1.30	0.37	0.00	0.103	0.000
cons_educ_5_6	-1.64	2.77	0.55	1.54	0.49	0.00	0.197	0.000
cons_inc_1	0.33	1.54	0.83	1.54	0.27	0.00	0.128	0.000
cons_inc_2	0.03	2.60	0.99	1.37	0.46	0.00	0.060	0.000
cons_inc_3	-2.12	2.65	0.42	1.64	0.47	0.00	0.170	0.000
cons_inc_4	-1.47	2.75	0.59	1.44	0.49	0.00	0.268	0.000
focus_day10	-2.28	1.29	0.08	1.26	0.22	0.00	0.704	0.000
focus_day15	-2.24	1.26	0.08	1.25	0.22	0.00	0.702	0.000

Notes: Forecasts' sample: January 2006 to July 2014. IPCA sample: December 2006 to June 2015

(103 observations). Robust standard errors (S.E.) from a GMM estimation. The column "OIR test"

denotes the p-values from the Over-Identifying Restriction (OIR) J-test due to Hansen (1982).

The column "No-Bias test" shows the p-values based on the null hypothesis $H_0: [\overline{k^h} = 0; \overline{\beta^h} = 1]$.

Forecast combination of consumer and market expectations

Next, we apply the Granger and Ramanathan (1984) forecast combination technique for the entire sample. It consists of a standard OLS regression (including an intercept) of IPCA inflation on the two consensus forecasts – consumer and market, respectively: cons_all and focus_day10. We run those regressions in two different ways: when the two slope coefficients are unrestricted and when they are restricted to add up to unity. Also, we cover two different sample periods: the whole sample and only the last five years. Results are presented in Table 5. Notice that, for the last 5 years, the consumer consensus is not significant, which does not happen for the whole sample.

Table 5 - Forecast Combination (Granger and Ramanathan, 1984)

$$IPCA_{t+12} = \alpha + \beta_1 cons_all_t + \beta_2 focus_day10_t + \varepsilon_{t+12}$$

Parameter	Unrestricted regression		Restricted regression	
	Full sample	Last 5 years	Full sample	Last 5 years
$\hat{\alpha}$	4.723 ** (2.192)	1.032 (2.627)	2.578 *** (0.851)	0.646 (0.769)
$\hat{\beta}_1$	-0.865 ** (0.378)	0.064 (0.396)	-0.703 ** (0.326)	0.084 (0.316)
$\hat{\beta}_2$	1.518 *** (0.336)	0.873 *** (0.277)	—	—
Adjusted R^2	0.385	0.279	0.348	0.289

Note: Consensus sample: January 2006 to July 2014. IPCA sample: December 2006 to June 2015.

Robust (HAC) standard errors in parentheses. Restricted regression imposes

$\beta_1 + \beta_2 = 1$. *, ** and *** indicate, respectively, significance at 10%, 5% and 1% level.

The estimated slopes can be interpreted as optimal weights under a MSE loss function. The combined (consumer-market) forecast is given by:

$$\widetilde{fcm}_t^h = \hat{\alpha} + \hat{\beta}_1 cons_all_t + \hat{\beta}_2 focus_day10_t.$$

Out-of-sample forecasting exercise

In this section, we conduct a truly out-of-sample forecasting exercise, incorporating what we have learned from the previous sections. In it, we compare different forecast methods by computing their out-of-sample Mean Squared Error (MSE) of forecasting. Our whole sample for the experiment runs from January, 2006 through July 2014 for the forecasts and from February, 2006 through June 2015 for the realizations of inflation, comprising 103 and 113 observations respectively. We leave the last 60 observations (5 years, comprising July, 2010 through June, 2015) for a pseudo out-of-sample evaluation of several forecasting strategies (or methods), which are estimated with a growing window. These methods include: a “best” model, chosen by Information Criteria, the Granger and Ramanathan (1984) forecast combination technique, the average forecast (or consensus forecast), the Bias-Corrected Average Forecast (BCAF), and the extended BCAF. For the last three strategies, we also present the MSE s by category of income and education.

The best model using information criteria is the $AR(1)$ model for the monthly inflation rate; see Cordeiro et al. (2015) and Gaglianone et al. (2016). The $AR(1)$ model for the monthly inflation rate y_t is as follows:

$$y_t = c + \beta y_{t-1} + \varepsilon_t. \quad (8)$$

From a sample with $t = 1, \dots, T$ observations, the respective estimates $[\widehat{c}; \widehat{\beta}]'$ are computed. The respective h -step-ahead forecast ($h > 1$) is given by

$$\widehat{y_{T+h}} = (\widehat{\beta})^h y_T + \sum_{i=1}^h \widehat{c} (\widehat{\beta})^{i-1}, \quad (9)$$

and the cumulative twelve-month rate ahead $y_{T+12}^{12m_rate}$, in percentage, is:

$$\widehat{y_{T+12}^{12m_rate}} = 100 \left(\left(\prod_{h=1}^{12} \left(1 + \frac{\widehat{y_{T+h}}}{100} \right) \right) - 1 \right). \quad (10)$$

Table 6 presents the comparison of the out-of-sample MSE of the different forecast strategies listed above. First, the MSE of the $AR(1)$ model is higher when compared to that of the Granger and Ramanathan combination of the consensus of consumers and of professional forecasters, and it is lower than that of the Average Forecasts – exceptions are the consensus for the highly educated forecasters, higher income forecasters, and professional forecasters (Focus Survey). Second, when we compare the MSE of the Average Forecast, BCAF and Extended BCAF, there is a clear *pecking order*: the extended BCAF is more accurate than the BCAF, which, in turn, dominates the Average Forecast. This validates the view that the bias corrections performed either by the BCAF, or by the extended BCAF, are a useful device for forecasting using surveys. Finally, when we compare the best forecasts for all consumers (Extended BCAF, cons_all) with the best forecasts for all professional forecasters (Extended BCAF, focus_day15), we observe a reduction of MSE in favor of professional forecasters of 22.5%, which is sizable. This happens despite the fact that, for consumers, we are averaging the forecast of approximately 1,500 individuals, whereas, for professional forecasters, we employ a little less than 100 individuals. This may be a sign that it matters to employ informed and well trained

professionals in forecasting inflation.

Table 6 - Mean Squared Error (MSE) – Out of Sample

	AR(1)	GR	Average Forecast	BCAF	Extended BCAF
cons_all	2.344 * [0.070]	0.921 [0.311]	3.406 * (0.000)	1.026 (0.129)	0.760
cons_educ_1_3	2.344 * [0.074]	0.921 [0.892]	10.148 * (0.000)	1.927 * (0.017)	1.417
cons_educ_4	2.344 * [0.056]	0.921 [0.257]	5.658 * (0.000)	0.863 * (0.092)	0.745
cons_educ_5_6	2.344 * [0.066]	0.921 [0.315]	2.287 * (0.008)	1.047 (0.196)	0.758
cons_inc_1	2.344 [0.128]	0.921 [0.345]	11.845 * (0.000)	1.149 * (0.001)	0.740
cons_inc_2	2.344 * [0.047]	0.921 [0.354]	4.650 * (0.000)	0.939 (0.103)	0.783
cons_inc_3	2.344 * [0.059]	0.921 [0.308]	2.784 * (0.001)	0.878 (0.251)	0.768
cons_inc_4	2.344 * [0.086]	0.921 [0.344]	1.523 * (0.050)	1.308 (0.174)	0.787
focus_day10	2.344 * [0.050]	0.921 * [0.098]	1.295 (0.289)	0.624 (0.454)	0.590
focus_day15	2.344 * [0.052]	0.921 * [0.099]	1.282 (0.296)	0.624 (0.443)	0.589

Note: Forecast evaluation sample = last 60 observations – July, 2010 through June, 2015. GR means the combined forecast of Granger and Ramanathan (1984), based on an OLS regression with intercept and "cons_all" and "focus_day10" forecasts as regressors. The second and third columns show [in brackets] the p-values of the equal variances' test of Diebold-Mariano (1995) between the AR(1) and GR, respectively, compared to the Extended BCAF (on each row). The fourth and fifth columns show (in parenthesis) the p-values of the equal-predictive accuracy test of Clark and West (2007), which compares the Average Forecast and the BCAF, respectively, with the Extended BCAF (on each row). In all cases, * indicates a rejection of the null hypothesis at a 10% level.

In order to check whether the differences in *MSE* observed in Table 6 are significant, we employ the equal-predictive-accuracy test of Clark and West (2007) for nested models. Results, also presented in Table 6, suggest that the average forecast and the BCAF have an inferior out-of-sample *MSE vis-à-vis* the extended BCAF forecast. Comparisons of the extended BCAF with the *AR*(1) model using a Diebold-Mariano test for equal variances shows that the former is statistically

superior to the latter (at the 10% significance level) in almost all cases. The Extended BCAF for the market forecasts also statistically improves (at a 10% level) the out-of-sample accuracy compared to the Granger and Ramanathan (1984) forecast combination approach.

All in all, if we had to suggest a single forecasting strategy for Brazilian inflation one-year ahead, we would suggest the use of extended BCAF based on the Focus Survey consensus (15th working day).

Rationality tests

In this section, we provide evidence that rationality test results based on a time-series of individual forecasts are very different from those using the time-series of the aggregate measure of consensus forecasts. When testing individuals separately, we find evidence of rationality for a subset of consumers, whereas we find the opposite in time-series of the consensus forecasts. This outcome is something that must be understood as we gather more frequent time-series observations in panels of forecasts.

Let y_t be the 12-month inflation rate measured by IPCA, $f_{i,t}^h$ be the respective inflation forecast of survey participant i formed at period $t - h$, and $\overline{f_{\cdot,t}^h}$ be the consensus forecast. The cross-section dimension is considered in two ways: (i) disaggregated data, with an individual OLS regression for each $i = 1, \dots, N^9$; and (ii) aggregated data (consensus forecast), with OLS regression. We focus on the widely employed rationality test of Mincer and Zarnowitz (1969), hereafter MZ, although other tests suggested in the literature could be further used (e.g. FIRE - Full-Information Rational Expectations tests from Coibion and Gorodnichenko, 2015). First we consider disaggregate data, with an individual OLS regression for each $i = 1, 2, \dots, N$. The individual-forecasts OLS regressions are given as follows:

$$y_t = \alpha_i + \beta_i f_{i,t}^h + \varepsilon_{i,t}, \quad (11)$$

where, y_t denotes observed inflation on period t , and $f_{i,t}^h$ denotes individual i forecast of y_t using only information up to period $t - h$. The Mincer and Zarnowitz (1969) test

⁹In each test with disaggregated data (individual OLS regressions), we only considered survey participants with more than 20 available forecasts.

is based on a Wald test of the joint null hypothesis of rationality, $H_0 : [\alpha_i = 0; \beta_i = 1]$ for each i . We then compute the proportion of agents for which we do not reject the null of rationality. Next, we consider aggregate data (consensus forecast), with OLS regression in time-series data. The consensus-forecast OLS regression is given by:

$$y_t = \alpha + \beta \overline{f_{:,t}^h} + \varepsilon_t, \quad (12)$$

where the rationality test is based on a Wald test of the joint null hypothesis $H_0 : [\alpha = 0; \beta = 1]$. In testing all the null hypotheses listed above we have employed robust (HAC) standard errors. Results for consumer forecasts are summarized in Table 7.¹⁰

Table 7 - Rationality (MZ) tests for consumers

Consensus	Individual Forecasts (% of rational)	Consensus Forecasts (MZ test, p-value)
cons_all	35%	0.000
cons_educ_1_3	26%	0.000
cons_educ_4	31%	0.000
cons_educ_5_6	40%	0.000
cons_inc_1	22%	0.000
cons_inc_2	31%	0.000
cons_inc_3	35%	0.000
cons_inc_4	37%	0.000

Notes: In the second column, the % of rational forecasters is based on p-value>0.05 in the MZ

individual rationality test and on consumers with at least 20 observations in time dimension.

Forecast sample: January 2006 to July 2014. IPCA sample: December 2006 to June 2015

(103 observations). Robust standard errors (S.E.) from a Newey-West covariance matrix.

When we consider tests using Mincer-Zarnowitz regressions with disaggregate data and individual OLS regressions for each i show that 35% of the consumers indeed pass rationality tests at the 5% significance level. Moreover, this percentage increases to 40% and 37% for the consensuses of higher educated consumers and

¹⁰We leave the rationality tests for market forecasters for future research, since the focus here is on leveraging the consumer data for forecasting purposes.

for those with higher income, respectively. However, when we analyze test results using the consensus forecasts with OLS regressions, the null is always rejected at the 5% level, which is consistent with results previously found in the literature, where rationality was rejected overwhelmingly in Mincer-Zarnowitz tests, and the results showed in Tables 3 and 4, in which the null of zero bias is strongly rejected.

As previously discussed, although approximately 100 professional forecasters provide more accurate inflation forecasts compared to roughly 1,500 consumers, the results from Table 7 reveal that there might be some useful information (for forecasting purposes) embodied in the consumer consensus forecast. In this sense, one might consider, for instance, taking into account only those rational consumers when forming a "filtered-consensus" forecast, thus, avoiding mixing information from the non-rational forecasters. We leave this for future research.

4 Conclusions

In this paper, we investigate whether or not combining forecasts from surveys of expectations is a helpful strategy for forecasting one-year ahead CPI inflation for Brazil. Combining forecasts has been a promising strategy at least since the seminal paper of Bates and Granger (1969). The techniques used in this paper have their roots in the pioneering work of Davies and Lahiri (1995) on what could be labelled *a panel-data approach to forecasting*. In this literature, some of the studies focused on forecast combination, e.g., Issler and Lima (2009), Gaglianone et al. (2011), Gaglianone and Lima (2012, 2014), Gaglianone and Issler (2015), and Lahiri, Peng, and Sheng (2015); see Baltagi (2013) for a broader discussion on this topic.

We investigate inflation forecasts from the *Brazilian Consumer Survey* conducted by the FGV-IBRE, which consists of monthly qualitative information from consumers in seven of the major capitals of the country, with a representative sample of the population and the rate of consumption of each capital with approximately 2,000 consumers. Our sample ranges from January 2006 up to May 2015, forming an unbalanced panel with $NT = 164,479$ responses ($T = 113$ months; and an average of $N = 1,456$ individuals per month). We also use The Focus Survey of the Central Bank of Brazil. It contains daily (working days) forecasts from roughly 250

registered institutions since 1999, the year when Brazil implemented its *Inflation-Targeting Regime*. About 100 of these institutions are actively feeding the data base with forecasts on any given day. Institutions include professional forecasters – commercial banks, asset management firms, consulting firms, non-financial firms or institutions, academics, etc.

Natural candidates to win a competition in the literature of surveys of expectations are the so-called consensus forecasts, i.e., the cross-sectional average among survey respondents. In an exploratory investigation, we first show that these consensus forecasts are a bias ridden version of the conditional expectation of one-year ahead inflation. The no-bias tests are conducted for the intercept and slope using the methods in Issler and Lima (2009) and Gaglianone and Issler (2015). The bias results reveal interesting features of the data: consumers systematically overpredict inflation (by 2.01 p.p., on average), whereas market agents overall underpredict it (by -0.68 p.p. over the same sample). Furthermore, we show that these biases lead to rejection in the Mincer-Zarnowitz tests of rationality using the consensus forecasts for consumers, although from 26% to 40% of consumers pass rationality tests at the individual level.

Next, we employ a pseudo out-of-sample analysis to evaluate different forecasting methods, consisting of a “best” model chosen by Information Criteria, the Granger and Ramanathan (1984) forecast combination technique, the consensus forecast, the Bias-Corrected Average Forecast (BCAF), and the extended BCAF. The results are interesting. The MSE of the $AR(1)$ model is higher when compared to that of the Granger and Ramanathan combination of the consensus of consumers and of professional forecasters, and it is usually lower than that of the Average Forecasts with a few exceptions. When we compare the MSE of the Average Forecast, BCAF and Extended BCAF, there is a clear *pecking order*: the extended BCAF is more accurate than the BCAF, which, in turn, dominates the Average Forecast. This validates the view that the bias corrections performed either by the BCAF, or by the extended BCAF, are a useful device for forecasting using surveys.

Finally, when we compare the best forecasts for all consumers (Extended BCAF, cons_all) with the best forecasts for all professional forecasters (Extended BCAF, focus_day15), we observe a reduction of MSE in favor of professional forecasters of

22.5%, which is sizable. This happens despite the fact that, for consumers, we are averaging the forecast of approximately 1,500 individuals, whereas, for professional forecasters, we employ a little less than 100 individuals. This may be a sign that it matters to employ informed and well trained professionals in forecasting inflation.

All in all, if we had to suggest a single forecasting strategy for Brazilian inflation one-year ahead, we would suggest the use of extended BCAF based on the Focus Survey consensus (15th working day).

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Appendix

GMM estimation with different set of instruments

In this section, we conduct the GMM estimation based on the following set of instruments: lagged aggregate forecasts; from one to five months.

Table A.1 - Extended BCAF estimation

Parameters	\widehat{k}^h	Robust	t-stat	$\widehat{\beta}^h$	Robust	t-stat	OIR test	No Bias test
Consensus		S.E.	p-value		S.E.	p-value	p-value	p-value
cons_all	-1.04	2.91	0.72	1.49	0.51	0.00	0.121	0.000
cons_educ_1_3	1.53	4.90	0.76	1.29	0.85	0.13	0.277	0.000
cons_educ_4	-2.83	3.68	0.44	1.89	0.65	0.00	0.297	0.000
cons_educ_5_6	-3.47	3.76	0.36	1.85	0.66	0.01	0.378	0.000
cons_inc_1	-2.20	2.65	0.41	1.95	0.46	0.00	0.132	0.000
cons_inc_2	-14.58	13.76	0.29	3.90	2.42	0.11	0.961	0.000
cons_inc_3	-7.75	5.31	0.14	2.61	0.93	0.01	0.899	0.000
cons_inc_4	-2.07	3.11	0.51	1.54	0.55	0.00	0.270	0.000
focus_day10	-3.04	1.50	0.04	1.39	0.26	0.00	0.994	0.000
focus_day15	-2.95	1.45	0.04	1.38	0.25	0.00	0.989	0.000

Notes: Forecasts' sample: January 2006 to July 2014. IPCA sample: December 2006 to June 2015

(103 observations). Robust standard errors (S.E.) from a GMM estimation of the BCAF.

Set of instruments: lagged forecasts, from one to five months. The column "OIR test"

denotes the p-values from the Over-Identifying Restriction (OIR) J-test due to Hansen (1982).

The column "No-Bias test" shows the p-values based on the null hypothesis $H_0 : [\overline{k}^h = 0; \overline{\beta}^h = 1]$.