Economic Modelling 64 (2017) 26–39

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.elsevier.com/locate/econmod

The new MIBA model: Real-time nowcasting of French GDP using the Banque de France's monthly business survey

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ARTICLE INFO

JEL classification:
C22
C52
C53
E37

Keywords:
Nowcasting GDP
Mixed-frequency data
Model selection
Real-time data

ABSTRACT

This paper introduces a new nowcasting model of the French quarterly real GDP growth rate (MIBA), developed at the Banque de France and based on monthly business surveys. The model is designed to target initial announcements of GDP in a mixed-frequency framework. The selected equations for each forecast horizon are consistent with the time frame of real-time nowcasting exercises: the first one includes mainly information on the expected evolution of economic activity, while the second and third equations rely more on information on observed business outcomes. The predictive accuracy of the model increases over the forecast horizon, consistent with the gradual increase in available information. Furthermore, the model outperforms a wide set of alternatives, such as its previous version and MIDAS regressions, although not a specification including also hard data. Further research should evaluate the performance of the MIBA model with respect to promising alternative approaches for nowcasting GDP (e.g. mixed-frequency factor models with targeted predictors), and consider forecast combinations and density forecasts.

1. Introduction

Models relying on the predictive information stemming from qualitative surveys have become increasingly popular for nowcasting real GDP growth rates (Banbura et al., 2011, 2013). It is wellknown in the literature (Rünstler and Sédillot, 2003; Forni et al., 2003; Baffigi et al., 2004; Banerjee et al., 2005) that business survey data ("soft data"), which usually display high correlation with GDP growth, convey less information about real activity than standard macroeconomic indicators ("hard data"). However, several recent studies (Hansson et al., 2005; Giannone et al., 2008; Banbura and Rünstler, 2011; Gayer et al., 2016) have pointed out that macroeconomic indicators appear less relevant than survey data for nowcasting purposes, once their publication lag is taken into account.[1] More precisely, business surveys offer several clear advantages over hard data. First, they provide a signal obtained directly from economic actors that reflects the short-term prospects of their own activity, sometimes with a forward-looking nature. Further, soft data are released with very short publication lags (usually at the end of the month covered by the survey), i.e. much sooner than the main macroeconomic indicators. Lastly, survey data are often subject to minor revisions only.

This paper contributes to the literature cited above by introducing and evaluating a new version of the Banque de France's Monthly Index of Business Activity nowcasting model (MIBA hereafter; in French, *Indicateur Synthétique Mensuel d'Activité*, ISMA), officially on duty since Q1 2013. Following the house's modeling tradition dating back to the 90s, the MIBA model is designed to nowcast French GDP using *exclusively* the information stemming from the Banque de France's business survey (EMC, *Enquête Mensuelle de Conjoncture*) on manufacturing industry and services.[2] Predictions are updated monthly on the basis of new EMC data inflows and are published in the Overview of the business survey since January 2000. Both the poor performance of

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[1] Giannone et al. (2008) use a model-based uncertainty measure to assess the news content of data inflows within a given month. They find the largest declines in uncertainty after the release of survey and financial data. Gayer et al. (2016) find that financial data are useful predictors of GDP during times of financial turmoils. Hansson et al. (2005) report that the inclusion of composite indexes of survey data into VAR models improves out-of-sample forecasts.

[2] This modeling choice reflects the goal set in the second half of the 90s with the implementation of the first version of the MIBA model, which was mainly to extract and evaluate the conjunctural information stemming from home-made survey data. The subsequent revisions of the model have focused further on nowcasting features, but have kept unaltered the restriction on the pool of predictors. In respect of this tradition, we thus constrain the new model presented in this paper to account for survey data stemming exclusively from the Banque de France's EMC.

http://dx.doi.org/10.1016/j.econmod.2017.03.003
Received 10 June 2016; Received in revised form 3 March 2017; Accepted 5 March 2017
Available online 18 March 2017
0264-9993/

the model during the Great Recession episode and the rise in recent years of a systematic predictive bias represent the main reasons underlying the re-assessment of the MIBA model. Several conceptual and econometric innovations at the heart of recent forecasting literature are introduced with the aim of upgrading the main features of the model and improving its predictive performance. These changes are presented in detail in the remainder of this paper.

First, we focus on a nowcasting model of GDP including a bunch of survey indicators parsimoniously selected through a GEneral-To-Specific approach (GETS hereafter; see Krolzig and Hendry, 2001). Indeed, the previous version of the model (Darné and Brunhes-Lesage, 2007) was *de facto* a mixed-frequency factor model of GDP (Marcellino and Schumacher, 2010; Altissimo et al., 2010), based mainly on the first factor extracted from monthly survey data on industry and additional survey indicators selected through GETS. However, this empirical strategy may suffer from two important drawbacks: i) the number of pooled indicators from which the factor is extracted is quite low, leading possibly to inconsistent estimates of the factors (Bai and Ng, 2002); and ii) this narrow set of pooled indicators includes several predictors *a priori* not relevant for modeling and nowcasting GDP, leading possibly to a deterioration of the predictive performance of the factor model in small samples (see Boivin and Ng 2006, for a more general discussion on this point). These issues motivate the approach, which excludes a factorization of predictors, implemented in the present paper.

Second, we make more explicit the official target of the MIBA model, which has always been implicitly the initial announcement of the real GDP growth rate, although in practice it was statistically and econometrically more consistent with a revised (or final) announcement of GDP. The latter is due to the fact that the GDP series used in the nowcasting equations was the latest available vintage series, hence accounting for revisions in past observations. Even though policy-makers and central bankers are mostly interested in final GDP announcements, the predictive accuracy of the MIBA model has been actually almost always assessed against initial announcements. This produced a hiatus between the target of the model and the data used to achieve it. A growing literature has dealt with this issue by taking full advantage of the vintage structure of real-time datasets. According to Koenig et al. (2003) and Clements and Galvão (2013), optimal and unbiased prediction of initial announcements of GDP can be achieved by implementing the so-called Real-Time Vintage (RTV) approach. In this paper, we follow this approach, and in doing so we set unambiguously the official target of our nowcasting model.

Finally, we deal with the well-known issues of mixed-frequency (variables sampled at different frequencies in the same econometric model) and ragged-edge data (partial information on predictors at the time of the nowcasting exercise) arising in nowcasting and forecasting models of GDP with survey predictors by implementing the “blocking” approach (Bec and Mogliani, 2015; Carriero et al., 2015). In its simplest and unrestricted version, this approach is equivalent to the Unrestricted MIxed DAta Sampling (U-MIDAS) approach recently proposed by Foroni et al. (2015), because blocking regressions resort to unrestricted linear lag polynomials whose coefficients can be estimated by OLS. However, we depart from the U-MIDAS approach by allowing for restrictions on exactly these coefficients. This solution has the advantage of avoiding over-parameterization of the nowcasting equations and can be readily accomplished by shrinking the coefficients towards zero using, for instance, a Bayesian technology (Carriero et al., 2015). Here we set zero-restrictions on the elements of the linear lag polynomials by implementing a selection algorithm based on the GETS approach (Hendry and Doornik, 2009).[3]

Model selection and estimation results suggest that the new MIBA nowcasting equations are broadly consistent with the time frame of a real-time nowcasting exercise. For the first forecast horizon, involving data available up to the first month of the quarter to be nowcast, only partial information on the current quarter is available, such that expectations on economic activity overwhelm information on past economic activity. However, for the second and third forecast horizons, involving respectively data up to the second and third month of the quarter to be nowcast, relevant information on the activity over the current quarter becomes available, outpacing forward-looking indicators. Out-of-sample evaluation suggests that the new MIBA model is reasonably accurate over a large evaluation period, in particular after the 2008–2009 economic crisis. Although the model is not able to capture the second consecutive strong contraction of French GDP in Q1 2009, it can track extremely well the recovery and the moderate growth observed since 2012. The predictive accuracy of the new MIBA model is tested against that of several alternative models, such as the previous version of the model, a MIBA model augmented with hard data, and MIDAS regressions. This benchmarking exercise reveals that our model broadly outperforms the competing models, and results are overall statistically significant.

The remainder of the paper is organized as follows. Section 2 discusses in greater detail the main features of the new MIBA model. In Section 3, we describe the data, the empirical strategy and the implemented model selection approach. Section 4 presents and discusses the estimation results. Section 5 reports a real-time out-of-sample evaluation, while Section 6 compares the predictive accuracy of the new MIBA model to that of alternative specifications. Finally, Section 7 concludes.

2. The new MIBA model: dealing with GDP revisions and monthly survey data

2.1. Nowcasting GDP in the presence of data revisions

It is well known that GDP undergoes numerous revisions, because initial announcements are only based on partial information that is progressively updated for the construction of final GDP values. Indeed, the French National Statistical Institute (INSEE hereafter) releases an initial estimate of GDP about 45 days after the end of the quarter. Since 1999, initial announcements are then revised during 3 years, according to an official schedule that involves the benchmarking of Quarterly National Accounts to Annual National Accounts (see Mogliani and Ferrière, 2016, for further details).[4]

From the point of view of the policy-maker, final GDP announcements represent a reliable picture of the true macroeconomic outlook and should be hence preferred/targeted by the forecaster. However, there is a large evidence on the effect of initial announcements of economic news on markets, so that the predictive accuracy of a forecasting model is often assessed when early official data are released. If the aim of the forecaster is to predict initial announcements of GDP growth, optimal and unbiased forecasts can be achieved by implementing the so-called Real-Time Vintage (RTV) approach (Koenig et al., 2003; Clements and Galvão, 2013). For the new version of the MIBA model, we chose to express plainly the nowcasting target in terms of initial announcements of GDP growth, and for that purpose we resort to the RTV approach.[5] Compared to the standard End-of-

[3] The same approach has been recently implemented by Hirashima et al. (in press), who refer to a mixed-frequency model with *Autometrics*-based model selection.

[4] In the case of France, initial announcements (also known as “preliminary estimates”) provide an early estimate of transactions on goods and services. “Detailed estimates” are released with a delay of about 85 days and add to the “preliminary estimates” by providing an early estimate of agent accounts. It is worth noting that in 2016 INSEE has started to release a “flash estimate” of GDP about 30 days after the end of the quarter, followed by the preliminary estimate and the detailed estimate, respectively, about 60 and 90 days after the end of the quarter. Before 1999, initial announcements were officially revised during 4 years.

[5] Our choice is in part supported by the findings reported in recent empirical literature. For instance, Minodier (2010) compares forecasting models of French GDP

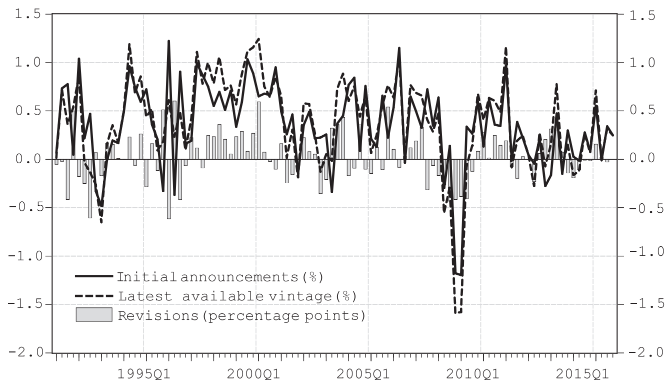

Fig. 1. French GDP: Initial announcements, latest available vintage, and revisions (Q1 1992–Q4 2015).

Sample approach (EOS), implemented in the previous version of the MIBA model and that makes use of the latest available vintage data to estimate model parameters and to compute the forecasts, the RTV approach consists of first matching early-release data when estimating regression parameters, and then using the latest available vintage data to compute the forecasts. For instance, consider a real-time data triangle of GDP vintages released with one quarter lag ($t+1$) with respect to the time index (t) of the initial announcement (see Croushore, 2011, p.75, for an illustration). In the simple case of a RTV-AR(p) nowcasting model, the vector of initial announcements drawn from the main diagonal of the real-time dataset (y_t^{t+1}, the dependent variable), and the vector of p adjacent diagonals ($y_{t-1}^t, \ldots, y_{t-p}^t$) are used to estimate the autoregressive parameters, and then the last p observations from the latest available vintage ($y_{T-1}^T, \ldots, y_{T-p}^T$) are used to compute the nowcast of the initial announcements for the current quarter ($\hat{y}_T^{T+1}$).

In Fig. 1 we report the series of initial announcements and the series of the latest available vintage (released in Q1 2016) as a proxy of final announcements, as well as the revisions computed as the difference between these two series as a proxy of total revisions. Revisions have been significantly positive, by 0.17 percentage point on average, over the Q1 1997–Q1 2001 period, marked by a strong GDP growth and a large diffusion of new information and communications technology, but very negative over the Great Recession episode spanning from Q2 2008 to Q3 2009 (−0.34 percentage point on average). The latter may be attributed to the fact that the models used in National Accounts to extrapolate indicators unavailable at the time of initial GDP estimates were only moderately able to capture the unexpected large swings in GDP growth.

2.2. Nowcasting GDP with monthly survey data

Due to the quarterly frequency of GDP series, the monthly predictors used in the MIBA model (business survey data) must be converted into quarterly data. An intuitive way to achieve this goal is to time-aggregate monthly data through a simple average, in order to match the sampling rate of lower-frequency data. However, this approach has the drawback of assigning the same weight to the high-frequency observations across the low-frequency window, which could be non-optimal compared to a different weighting scheme (Andreou et al., 2010). Further, and more importantly, the ragged-edge data issue arises when survey data covering the quarter to be predicted are partially available at the time of the forecasting exercise (Wallis, 1986). An alternative method, commonly used to address this issue, is to fill in missing observations by forecasting explanatory variables through the so-called "bridge" models (Rünstler and Sédillot, 2003; Baffigi et al., 2004; Diron, 2008; Darné and Brunhes-Lesage, 2012). However, besides the inconvenience of having to forecast explanatory variables, quarterly averages of monthly indicators have the additional drawback of representing a non-optimal treatment of the available information. For instance, let us consider forward-looking survey indicators, such as expected production and order books. The information available at the beginning of the quarter may be more useful for forecasting GDP over a given quarter, rather than a quarterly average which would include some information about the following quarter. In this respect, MIDAS regressions (Clements and Galvão, 2008, 2009; Kuzin et al., 2011; Ferrara et al., 2014) and factor models with Kalman filter (Giannone et al., 2008; Rusnák, 2016) have been successfully implemented for nowcasting and forecasting quarterly GDP growth in the presence of mixed-frequency and ragged-edge issues.

The econometric approach implemented in the present paper departs from these approaches. To address the mixed-frequency and ragged-edge issues, we implement so-called "blocking", a technique recently discussed by Bec and Mogliani (2015) and Carriero et al. (2015), and also implemented in the case of France by Dubois and Michaux (2006); Bessec (2010) and Minodier (2010) and for the Euro Area by Gayer et al. (2016). The primary ingredient of this approach consists of matching the high frequency information of the predictors with the low frequency nature of the response variable. Let us set the unit of time (t) to a quarter, such that the observations for the response (quarterly) variable are indexed with $t = 1, 2, \ldots$, while the observations for the monthly predictors are indexed with $t = 1/3, 2/3, 1, 4/3, \ldots$ Further, let us define the monthly lag operator $L^{1/3}$, such that, for a given quarter t, $L^{2/3}x_t = x_{t-2/3}$ defines the observation of x in the first month of the quarter, $L^{1/3}x_t = x_{t-1/3}$ defines the observation in the second month, and $L^{0/3}x_t = x_t$ defines the observation in the third month. This approach allows the forecaster to take into account the observations that are actually available at the time of the nowcasting exercise, and to use the most relevant information conditional on the date at which the nowcast is performed. More formally, let us assume a mixed-frequency RTV model of initial announcements of the GDP growth rate for quarter t released at quarter $t+1$, denoted y_t^{t+1}, conditional on $p \geq 1$ autoregressive lags $(y_{t-1}^t, \ldots, y_{t-p}^t)'$, and m lags of w monthly predictors (assumed unrevised for ease of analysis), where m is typically set as $m \in (6, 9, 12)$. We can then write the following three nowcasting equations, each one embedding information available up to the end of the first (M1), second (M2), and third (M3) month of quarter $t = T-1$, respectively:

$$\text{M1} \equiv y_t^{t+1} = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i}^t + \sum_{s=1}^{w} \sum_{j=3}^{m} \gamma_{s,j} L^{(j-1)/3} x_{s,t} + \epsilon_t \tag{1a}$$

$$\text{M2} \equiv y_t^{t+1} = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i}^t + \sum_{s=1}^{w} \sum_{j=2}^{m} \gamma_{s,j} L^{(j-1)/3} x_{s,t} + \epsilon_t \tag{1b}$$

$$\text{M3} \equiv y_t^{t+1} = \beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i}^t + \sum_{s=1}^{w} \sum_{j=1}^{m} \gamma_{s,j} L^{(j-1)/3} x_{s,t} + \epsilon_t \tag{1c}$$

According to the RTV approach (see Section 2.1), a nowcast of the initial announcement y_T^{T+1} can be then obtained from:

$$\hat{y}_T^{T+1} = \hat{\beta}_0 + \sum_{i=1}^{p} \hat{\beta}_i y_{T-i}^T + \sum_{s=1}^{w} \sum_{j=h}^{m} \hat{\gamma}_{s,j} L^{(j-1)/3} x_{s,T} \tag{2}$$

where $h = \{1, 2, 3\}$, depending on the available information on the current quarter to be nowcast.

Without further assumptions and restrictions on the lag polynomials $\gamma(L^{1/3})$, the mixed-frequency approach presented above belongs to the Unrestricted MIDAS (U-MIDAS) class of regression models re-

(*footnote continued*)
targeting either final or initial announcements of GDP. She shows that the predictive accuracy is significantly improved by the implementation of a RTV approach when initial GDP announcements are the target of the forecaster. Similar results are obtained by Koenig et al. (2003) and Clements and Galvão (2008, 2009) on U.S. data, in a similar context of real-time forecasting.

cently proposed by Foroni et al. (2015), which is in turn a special case of the general MIDAS regression with step-weighting functions (Forsberg and Ghysels, 2007). Indeed, regressions (1a)–(1c) do not resort to functional lag polynomials, but rather to unrestricted linear lag polynomials, whose coefficients can be estimated by OLS.

As suggested by Bec and Mogliani (2015), the main advantage of this approach with respect to alternative methods, such as MIDAS regressions resorting to functional lag polynomials, is that the regression model presented above is linear, which is convenient for both the estimation through standard OLS techniques and the implementation of model selection algorithms. Thus, the blocking approach arises from the combination of an unrestricted mixed-frequency model and a model reduction technique, the latter setting restrictions on the elements of the linear lag polynomials $\gamma(L^{1/3}) = \sum_j^m \gamma_j L^{(j-1)/3}$ (see also Section 3.2). Further, compared to bridge models, this approach allows the nowcaster to directly exploit the partially available data at any time, with no need to extrapolate the missing information. However, this approach may have a normative drawback if the equations are different: it would be more difficult to interpret nowcast revisions across the same quarter when a different equation, rather than a single and identical equation, is used at each forecast date. In Section 4 we shall see that the selected equations are sequentially quite similar, so that it is relatively easy to track and explain the source of nowcast revisions. This point will be further explored in Section 5.3.

3. Estimating the new MIBA model: data and model selection strategy

3.1. GDP and survey data

In this section, we provide additional details on the variables used in the MIBA model. With respect to real GDP series, seasonally-adjusted vintages of quarterly growth rates are collected in a real-time data triangle, with initial announcements (the main diagonal) spanning from Q1 1992 to Q4 2015. Vintages are provided by INSEE and refer to the series of “preliminary estimates” of GDP (see footnote 7). With respect to survey data, monthly series are drawn from the manufacturing industry and services sections of the EMC survey. The survey is conducted each month by the Statistics Directorate of the Banque de France over about 9000 firms. It is designed to collect managers' and entrepreneurs' opinions about the month-on-month evolution of past and expected activity, using a rating scale with seven gradations (three gradations either side of the normal level). “Balances of opinion” are hence computed as the sum of positive and negative responses, weighted by the size of each firm and adjusted for the value-added of each sector. Finally, the series are seasonally adjusted and normalized to range between −200 and +200. The EMC survey is then released to the public by the end of the first working week of the following month, although preliminary data are available by the end of the month to the staff of the Banque de France for internal use.[6]

Fourteen balances of opinion relate to the total manufacturing industry, which covers the four main manufacturing sub-sectors according to the INSEE's NAF-NACE Rev.2 nomenclature (agri-food industry, capital goods, transport equipment and other manufactured goods; only the low-weighted sub-sector “Manufacture of coke and refined petroleum products” is not covered by the survey), and have been collected since 1987. Seven balances of opinion relate to total services and have been collected since 1989. Overall, a total of 21 (14 + 7) indicators can be used in the present analysis. See Table A1 in the Appendix for more details. The balances of opinion are mostly revised once, because late responses (usually collected above the deadline) and, to a lesser extent, variations in the seasonal factors can be accounted for in the following monthly releases. However, these revisions are typically very small, so that we can consider our survey data as unrevised without loss of generality.

3.2. Model selection

It is easy to check that Eqs. (1a)–(1c) can be heavily parameterized for a large number of regressors $k = [w(m - h + 1) + p + 1]$, where w, m, p, and h are defined in Section 2.2, leading to in-sample overfitting and poor out-of-sample performance compared to more parsimonious models, such as MIDAS and factor-MIDAS regressions (Marcellino and Schumacher, 2010; Kuzin et al., 2013). Hence, either an aggregation or a shrinkage method is strongly required for dealing with the curse of dimensionality (large number of parameters to be estimated relative to the number of observations) implied by the unrestricted regressions described in Section 2.2.

In this study, model reduction is performed in an automatic fashion, following the GETS approach popularized by Krolzig and Hendry (2001) (see also Hoover and Perez, 1999), by setting zero-restrictions on the elements of the linear lag polynomials $\gamma(L^{1/3})$ in Eqs. (1a)-(1c). The aim is to obtain a model that is both adequately specified, i.e. no relevant explanatory variable are omitted, and parsimonious, i.e. only redundant variables are excluded. It follows that the blocking approach considered here is a special case of the U-MIDAS regression with restricted linear lag polynomials, where linear restrictions are set by a GETS algorithm. In the present study, the GETS approach is implemented using the *Autometrics* algorithm (Doornik, 2009; Hendry and Doornik, 2009), which can choose efficiently and in a reasonable time a subselection of paths from the total 2^k paths, even when the number of predictors is larger than the sample size (see also Hirashima et al., in press, for a recent application).

However, the automatic selection approach is here backed by the “expert opinion” of the forecaster. Indeed, judgmental arguments can be advocated in order to fine-tune the automatically selected equations, especially in case the outcome of the selection algorithm does not reflect reasonable priors on the stability and the interpretation of the model. With this aim in mind, we proceed as follows. From the automatic selection outcome, we may sequentially adjust the retained equations by: i) discarding misleading information provided by linear combinations of variables suspected to accommodate particular features of the data;[7] ii) taking advantage of the latest information, since selected equations are expected to embed the most recent available monthly information; iii) minimizing model changes, in order to avoid large nowcast revisions over the quarter due to important specification differences between the equations used at each forecast date; iv) testing for statistical adequacy through a battery of recursive regressions and Chow tests; and v) favoring economic interpretation, because final selected specifications are expected to be economically, rather than purely statistically, interpretable.

A detailed discussion on the pros and cons of this approach is provided by Bec and Mogliani (2015), and we hence refer the reader to that contribution for further considerations. Although the way these conditions affected the selection of the MIBA equations is rigorously described in Section 4, this strategy may not be exempt from subjectivity issues, leading paradoxically to a deterioration of the nowcasting performance of the selected specifications compared to alternatives selected through a purely automatic approach. To shed

[6] Survey data on the construction sector, as well as on retail and wholesale trade, are also available from the Banque de France. However, the series start in 2009, 1993 and 1996, respectively. Further, data on wholesale trade are released on a quarterly basis. Yet, the use of trade indicators may appear not suitable for modeling GDP from a supply-side perspective, as in the case of the MIBA model.

[7] For instance, since the Great Recession episode, it has been frequently noted by the authors that models selected through automatic procedures tend to include linear combinations of variables that lead to a better fit over few observations (Q4 2008 and Q1 2009, in particular), where GDP variations have been very strong and forecasting models have often reported substantial forecast errors, but are difficult to interpret economically.

Table 1
The new MIBA nowcasting equations (Q1 1992–Q4 2015).

M1			M2			M3		
Variable	Coefficient	*t*-stat	Variable	Coefficient	*t*-stat	Variable	Coefficient	*t*-stat
Intercept	13.07	3.42	*Intercept*	5.56	1.44	*Intercept*	6.46	1.67
	(3.82)	[0.00]		(3.84)	[0.15]		(3.87)	[0.10]
y_{t-1}^{t}	-0.41	-5.00	y_{t-1}^{t}	-0.37	-5.12	y_{t-1}^{t}	-0.39	-5.18
	(0.08)	[0.00]		(0.07)	[0.00]		(0.07)	[0.00]
$\text{EVLIV}_{t-2/3}$	2.26	4.46	$\text{EVLIV}_{t-1/3}$	2.00	5.18	EVLIV_{t}	0.99	2.61
	(0.51)	[0.00]		(0.39)	[0.00]		(0.38)	[0.01]
$\text{PREVPRO}_{t-2/3}$	3.81	5.78	$\text{PREVPRO}_{t-1/3}$	1.96	3.06	$\text{EVLIV}_{t-1/3}$	2.04	5.23
	(0.66)	[0.00]		(0.64)	[0.00]		(0.39)	[0.00]
			$\text{EVLIV}_{t-2/3}$	2.31	4.91	$\text{EVLIV}_{t-2/3}$	2.80	6.61
				(0.47)	[0.00]		(0.42)	[0.00]
$dummy_{09Q1}$	-98.0	- 3.61	$dummy_{09Q1}$	-79.9	-3.06	$dummy_{09Q1}$	-92.6	-3.53
	(27.2)	[0.00]		(26.2)	[0.00]		(26.2)	[0.00]
Adj-R^2	0.66		Adj-R^2	0.70		Adj-R^2	0.69	
σ_ϵ	24.92		σ_ϵ	23.60		σ_ϵ	23.92	
BIC	9.45		BIC	9.38		BIC	9.41	
Normality	4.57	[0.10]	Normality	1.93	[0.38]	Normality	1.03	[0.60]
AR(4)	0.58	[0.68]	AR(4)	2.45	[0.05]	AR(4)	1.31	[0.27]
Het	0.43	[0.79]	Het	0.23	[0.95]	Het	0.31	[0.90]

Notes: GDP growth rates are expressed in basis points. Standard errors in parentheses, *p*-values in brackets. σ_ϵ is the regression standard error. BIC is the Schwarz information criterion. "Normality" denotes the Bera-Jarque test for residual normal distribution. AR(4) denotes the Breusch-Godfrey test for residual serial correlation up to order p=4. "Het" denotes the Breusch-Pagan-Godfrey test for heteroskedasticity.

light on this issue, in Section 6 we compare our out-of-sample results to those from competing models, whose specifications are obtained either by optimizing the BIC or through a full-*Autometrics* approach.

4. Estimation results

This section presents the new MIBA equations as they are currently used by the staff of the Banque de France. The specifications were selected by the end of 2012 following the approach described in Section 3.2 and setting m=6. For ease of exposition, the reported estimation results use a sample spanning from Q1 1992 to Q4 2015 (T_{in} = 96 observations). The selected specifications include the first lag of GDP (y_{t-1}^{t}) and a dummy variable for Q1 2009 (taking value 1 in Q1 2009, and 0 elsewhere). The latter proved to be necessary to neutralize parameter instability (tested through the 1-step recursive Chow test), or more specifically a break in the constant term and the coefficient of lagged GDP, observed from the first quarter of 2009 onwards. This date coincides with the second consecutive quarter of deep recession in France during the Great Recession episode, which is inaccurately fitted by our equations. The equations are presented in Table 1 and are extensively discussed in the following sections.

4.1. M1 equation

The M1 equation includes the balance on changes in deliveries for the first month of the quarter ($\text{EVLIV}_{t-2/3}$), and the balance on expected changes in production for the first month ($\text{PREVPRO}_{t-2/3}$) (see Section 4.4 for a discussion of the issue of lagged GDP, which is actually unknown at the end of the first month of the quarter due to publication lags). This equation is therefore partially forward-looking, consistent with the time frame of the estimation (the end of the first month of each quarter). The coefficient of the expected changes in production being almost twice as large as that of changes in deliveries, we can interpret the equation as a simple average of deliveries of the first month and projected deliveries for the next two months.

The selection algorithm automatically selected two additional balances: changes in deliveries for the first month of the previous quarter ($\text{EVLIV}_{t-5/3}$) and changes in overall orders for the first month of the previous quarter ($\text{EVCOM}_{t-5/3}$). The two variables being highly pairwise correlated (0.91), the size and sign of their estimated coefficients (−2.90 and +3.17, respectively, with the hypothesis of equal coefficients not rejected at 10% level) suggested that a linear combination of these balances was actually selected. Indeed, the exclusion of one of these two balances from the equation implied a fall in the statistical significance of the other, which means that their individual contribution to the nowcasting equation is negligible. In the interest of parsimony, we therefore excluded these two balances from the M1 equation.

4.2. M2 equation

The M2 equation includes the balances on changes in deliveries for the first and second month and expected changes in production for the second month. This equation presents an obvious similarity with the previous equation (the same balances of opinion). The size of the estimated coefficients is almost the same across the selected predictors (approximately 2) and close to that observed for the coefficients entering the M1 equation. Indeed, we can assume that the balance on expected changes in production in the first month, entering the M1 equation with an estimated coefficient around 4, is a proxy for the balances on changes in deliveries in the second month and expected changes in production in the second month, both entering the M2 equation with estimated coefficients around 2.

As in the case of the M1 equation, the algorithm initially selected two additional balances: the average capacity utilization rate for the second month of the current and previous quarter ($\text{TUC}_{t-1/3}$ and $\text{TUC}_{t-4/3}$, respectively). Given the statistical properties of this series (a deep trough corresponding to the Great Recession episode) and the estimated level coefficients (+8.67 and −6.53, respectively, with the hypothesis of equal coefficients not rejected at 5% level), this combination of balances can be interpreted as a first difference, which was obviously selected by the algorithm in order to accommodate the large swings in GDP growth observed between 2008 and 2009. Again, in the interest of parsimony we excluded these two balances from the M2 equation.

4.3. M3 equation

Finally, the M3 equation includes the balances on changes in deliveries for the three months of the quarter. It is worth noting that the estimated coefficient for the third month is roughly half the size of those for the first two months. This result suggests that survey data collected over the third month of the quarter provide much less valuable information about the current economic activity than survey data collected over the previous months. In fact, the balance for the last month of the quarter was not initially included in the M3 equation selected by the automatic procedure, which preferred the $\mathrm{PREVPRO}_{t-1/3}$ balance. We nevertheless preferred to include EVLIV_t, which allows us to overcome the problem of computing the third nowcast based on an equation that presents exactly the same variables as the M2 equation, disregarding therefore the information stemming from survey data collected over the third month of the quarter (even if we clearly observe that, in practice, moderate new information is provided).

4.4. A discussion of the estimation results

The inclusion of the first lag of GDP in the selected equations may raise two issues, especially in a context of real-time nowcasting. First, publication lags imply that the first lagged value of GDP (y_{T-1}^{T}) is not known when nowcasts are performed through the M1 equation. Indeed, GDP is released roughly 10 to 15 days after the release of the monthly business survey for the first month of the current quarter. Second, the presence of an autoregressive term with a negative and a statistically significant coefficient (around -0.4), introduces a correction mechanism that operates systematically in each nowcasting exercise. In practice, we may suppose that this term essentially reflects the way the growth rate reverts to a “norm” after a one-off shock to GDP (for instance, a sharp falloff in construction production due to adverse weather conditions or a sudden boom in the production of transport equipment due to the manufacturing of high value-added goods by Airbus, both offset in the following quarter), and it may then be expected that a quarter-on-quarter correction would not be relevant in the event of a strong increase or a sharp drop in GDP related to a cyclical phase of acceleration or slowdown of the economic activity (a recession, for example). These issues may be arbitrarily addressed by dropping the lag of GDP from the equations, but this would lead mechanically to a strong autocorrelation of residuals. Hence, the solution adopted here consists of keeping the first lag of GDP in the selected equations and using the GDP growth of the previous quarter predicted by the M3 equation when nowcasting GDP in the current quarter with the M1 equation. Forecast errors are therefore expected to be fairly larger for M1 predictions, because the model additionally embeds the uncertainty surrounding the nowcast of the previous quarter's GDP. This point is discussed in the next section.

The specifications described in Sections 4.1, 4.2, and 4.3 point to a high model consistency across the quarter. The information used in the M1 equation focuses on contemporaneous information and information on growth prospects. However, in the M2 equation the contemporaneous information becomes more substantive, while forward-looking information carries progressively less weight (the estimated coefficient is halved) until it is definitely discarded from the M3 equation. A remark may be made on the presence of the balance on changes in deliveries in all the equations, rather than the balance of opinion on changes in production (EVPRO), i.e. a proper measure of actual output. In practice, these two balances are strongly correlated (the pairwise correlation index is about 0.94), and both track cyclical GDP growth relatively well. However, the former has the statistical and economic advantage of being slightly less volatile than the latter when there is a slowdown in economic activity, which also means fewer false alarms of drops in output and GDP. This statistical feature can be explained by the business accounting data available to managers and entrepreneurs when filling the monthly survey. Indeed, the balance on changes in deliveries essentially reflects changes in firms' sales, which is a fairly accurate quantification of the monthly evolution of activity, while the balance on changes in production incorporates a higher level of uncertainty, due to the absence of accurate and readily available information on current output levels.

Finally, we observe that only balances of opinion from surveys on the manufacturing industry are included in our nowcasting equations. Thus, as often observed in the literature, no balances of opinion on services are selected, in spite of the increasingly significant role played by services in the French economy. This is likely due to the fact that the manufacturing industry is a sector showing sizable output swings and spillover effects on other sectors, such as services to firms. Indeed, the correlation index between the growth rate of GDP and that of manufacturing output is 0.89 over the estimation period. In the present study, the absence of balances on services mostly reflects the output of the automatic selection. In practice, we observed that a bunch of balances of opinion on services (mainly, the balance on expected activity in services, competing with the balance on expected production) were not selected only due to a slight in-sample statistical superiority of specifications including balances of opinion on the manufacturing industry.[8]

5. Real-time out-of-sample evaluation

5.1. Design of the nowcasting experiment

In this section we report an evaluation of the nowcasting performance of the MIBA model. Since this model is currently used by the staff of the Banque de France, the out-of-sample exercise must be designed to replicate the actual conditions of the real-time forecaster. In this respect, one problem with the model described in Section 4 is that its selection is performed using the information available up to the end of 2012, so that the out-of-sample evaluation over previous periods would be affected, for instance, by the issue of data mining (see Clark, 2004). In order to address this issue and to account for the uncertainty surrounding the forecasting activity in real-time, we perform a model selection (along the lines suggested in Section 3.2) every 5 years, starting from Q4 2001 and updating the specifications in Q4 2005 and Q4 2009, using actually available information only. This strategy is in part consistent with a record of two previous official revisions of the MIBA model, performed in 2001–2002 and 2006–2007 (see Darné and Brunhes-Lesage, 2007). Our main aim is to avoid frequent updating of the specifications, since professional forecasters usually dislike an overly frequent switching of forecasting models. The last revision of the model in Q4 2009 is instead consistent with the response of the forecaster to the well-known shock that the Great Recession episode

[8] The previous version of the MIBA model included the balance of opinion on changes in activity in the services sector. Further, Bessec (2010) finds that balances of opinion from the INSEE survey on services and construction may enter nowcasting equations. However, both implemented the EOS approach to nowcast French GDP, which suggests that survey data on sectors other than manufacturing (such as services and construction) may be useful for modeling and predicting final, rather than initial, announcements of GDP. To investigate this point, in the working paper version of the present article we reported experiments performed with alternative specifications including balances of opinion on services and based on the EOS approach. Out-of-sample results suggested that our MIBA model outperforms the alternative model when forecast errors are computed with respect to initial announcements of GDP, but not when errors are computed with respect to the latest available GDP vintage. Further, this finding suggests that survey data on services may display some predictive content on total GDP revisions (see Mogliani and Ferrière, 2016).

represented on both in-sample and out-of-sample performance of forecasting models almost worldwide. We expected the specifications selected during this last revision to be very close to those of the current MIBA model. In practice, the selection process provided exactly the same specifications as those reported in Section 4.[9]

The out-of-sample performance of the selected equations is assessed over the period spanning from Q1 2002 to Q4 2015 ($T_{oos} = 56$ observations). We also focus on two sub-periods (Q2 2007–Q4 2015 and Q2 2009–Q4 2015), in order to account for potential under-performance due, for instance, to the transition of quarterly accounts from constant prices to chain-linked prices in Q1 2007 and to the effects of the Great Recession episode. Nowcasts are computed recursively over the hold-out sample, and regression parameters are updated at each step according to an expanding hold-in sample (starting in Q1 1992). Finally, the predictive accuracy of the MIBA model is assessed according to Mean Absolute Forecast Error (MAFE) and Root Mean Squared Forecast Error (RMSFE) criteria. Bootstrap standard errors for these criteria are also computed.

5.2. Results

Evaluation results are reported in Table 2. As expected, the predictive accuracy of the nowcasting model increases over the quarter, as the information stemming from surveys also increases. The improvement between M1 and M3 is quantitatively substantial over the whole sample (about 14% according to the RMSFE and 17% according to the MAFE), and it tends to increase when sub-samples are considered (about 20%). It is worth noting that the lower accuracy of the M1 equation may be in part attributed to the fact that the nowcasts embed the prediction of the first lag of GDP ($\hat{y}_{T-1}^{T}$) provided by the M3 equation in the previous quarter. However, compared to a *pseudo*-M1 equation incorporating the actual information about the previous quarter's GDP growth (which is not known in a real-time exercise), our findings point to a moderate predictive loss for the M1 equation. This suggests that the approach implemented in the present paper does not introduce a significant bias in the M1 nowcasts. Bootstrap standard errors are rather narrow, ranging between 0.02 and 0.05 for both MAFE and RMSFE. Although these figures should be interpreted with care, because their size could be affected by the short length of both the estimation and evaluation periods, they are broadly in line with findings reported elsewhere (see, for instance, Stock and Watson, 2002, for the U.S., and Bec and Mogliani, 2015, for France).

Nowcasts and prediction errors are graphically presented in Fig. 2, while both empirical and theoretical error densities are presented in Fig. A1 in the Appendix. From Fig. 2a and 2b, we note that forecast errors are overall small and show an uneven pattern around zero, with errors from M2 and M3 equations substantially less pronounced than those from the M1 equation. A sequence of over-predictions can be nevertheless observed from 2002 up to mid-2003 and between 2013 and 2014. It is worth noting that the model is extremely accurate in predicting the sharp drop observed in Q4 2008, but it broadly over-predicts the growth rate in Q1 2009, partly because of the correction induced by the negative autoregressive term.

5.3. The contribution to nowcast revisions

As pointed out in the previous paragraph, nowcasts are subject to revisions across the same quarter. Revisions can be decomposed into two factors: changes in the model and new data inflows. The former is a natural consequence of the blocking approach, since under this framework the nowcasting equations are expected to evolve according to the availability of monthly data. The latter is instead a consequence of the nowcasting design of the MIBA model, which is expected to account for real-time information stemming from data inflows. These two factors can be quantified by approximating the nowcast revisions with the contribution of new information to each nowcast Banbura et al. (2011). Let us consider two consecutive nowcasting equations (such as equations M1 and M2), so that we also have two, possibly different, consecutive predictions. Our aim is to determine how much of the revision observed between the first and the second prediction can be explained by the contribution of the most recent data inflows. One way to achieve this goal is to estimate the non-redundant information conveyed by predictors entering the second equation only, conditional on both the common information and the information conveyed by predictors entering the first equation only (see a formal proof in the Appendix).

Results are presented graphically in Fig. 3. From Fig. 3a, revisions between M1 and M2 are quite large ($\sigma = 0.2$), but they can be broadly explained by the contribution of new data inflows and GDP updates. The former reflects the flow of information stemming from predictors belonging to the M2 equation only, while the latter reflects the update of GDP for quarter $T-1$ from an estimated value used for M1 nowcasts to an actual value used for M2 nowcasts (see Section 4.4 for a discussion). With some noticeable, although rare, exceptions, the contribution of new data inflows explains the largest share of nowcast revisions. This finding can be interpreted as the moderate role played by GDP updates, and confirms the out-of-sample results discussed in Section 5.2 and reported in Table 2 (*pseudo*-M1). Fig. 3b points to small nowcast revisions between M3 and M2 ($\sigma = 0.1$), again explained mostly by the contribution of new data inflows. This finding is also consistent with the results reported in Table 2.

6. Benchmarking the new MIBA model

In this section we compare the predictive performance of the new MIBA model to that of a set of alternative models. Among them, a natural competitor is represented by the previous MIBA model. However, we also consider alternative mixed-frequency approaches, such as MIDAS regressions and a full-*Autometrics* selection that excludes the intervention of the forecaster on the automatic model selection (see Section 3.2), as well as a MIBA model augmented with hard data. Finally, we compare the out-of-sample performance of our model to a pool of alternative professional forecasters provided by the Consensus Forecasts. It is worth noting that in order to obtain a fair comparison and to avoid data mining, the alternative econometric models (excluding the previous MIBA) are selected following the strategy described in Section 5.1.

Comparison is carried out by computing relative MAFE and RMSFE values over the whole evaluation sample and the two sub-periods defined in Section 5.1. The benchmark is represented by our MIBA model, such that a value less than one means that the MIBA model outperforms the competitor. Further, to account for sample uncertainty underlying the observed forecast differences, we report results for the Diebold and Mariano (1995) and West (1996) test (DMW hereafter), which posits the null hypothesis of an unconditional equal predictive accuracy (EPA hereafter) between the MIBA model and the alternative models. The resulting test statistic is computed on both MAFE and

[9] More precisely, we started with a specification selected using data available up to Q4 2001, and we computed recursively real-time nowcasts for the quarters Q1 2002–Q4 2005, with regression parameters updated recursively at each quarter according to an expanding window; then, we reselected a new specification using data available up to Q4 2005, and we computed recursively real-time nowcasts for the quarters Q1 2006–Q4 2009; finally, we reselected the last specification using data available up to Q4 2009, and we computed recursively real-time nowcasts for the quarters Q1 2010–Q4 2015. The drawback of this design is that the results (model selection and predictions) may depend on the choice of the re-specification dates. To address this issue, we evaluated the stability of the selected nowcasting equations by allowing for a re-specification of the model every four quarters, i.e. model selection was performed using data available up to Q4 2001, then up to Q4 2002, and so on up to Q4 2014. Results (not reported) suggest that the baseline specifications of the MIBA model are broadly stable overtime, as they are very close to those obtained by allowing for a fairly frequent re-specification of the nowcasting equations. It follows that real-time nowcasts are only marginally affected by changes in the design of the nowcasting experiment.

Table 2
Real-time out-of-sample evaluation (Q1 2002–Q4 2015).

Equations	Q1 2002–Q4 2015		Q2 2007–Q4 2015		Q2 2009–Q4 2015	
	MAFE	RMSFE	MAFE	RMSFE	MAFE	RMSFE
M1	0.23 (0.03)	0.29 (0.04)	0.21 (0.03)	0.28 (0.05)	0.18 (0.03)	0.22 (0.04)
M2	0.21 (0.02)	0.27 (0.03)	0.18 (0.02)	0.23 (0.03)	0.15 (0.02)	0.19 (0.03)
M3	0.19 (0.02)	0.25 (0.03)	0.16 (0.03)	0.23) (0.04)	0.14 (0.02)	0.17 (0.03)
pseudo-M1	0.20 (0.02)	0.27 (0.03)	0.21 (0.03)	0.27 (0.04)	0.17 (0.02)	0.20 (0.03)

Notes: *pseudo*-M1 denotes the M1 model embedding the actual values for the first lag of GDP (y_{T-1}^{T}). Standard errors (in parentheses) are computed through non-parametric bootstrap with 10,000 draws.

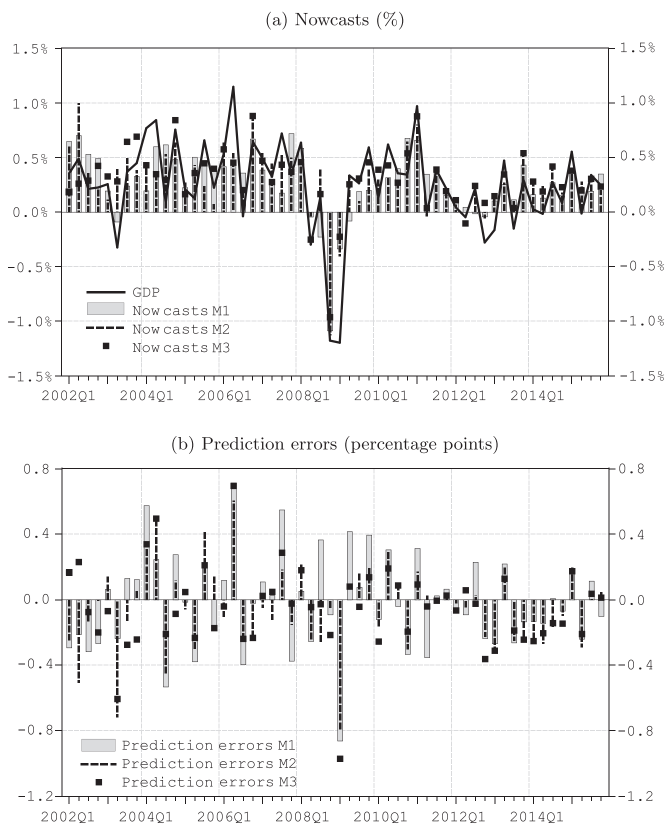

Fig. 2. MIBA nowcasts and prediction errors (Q1 2002–Q4 2015).

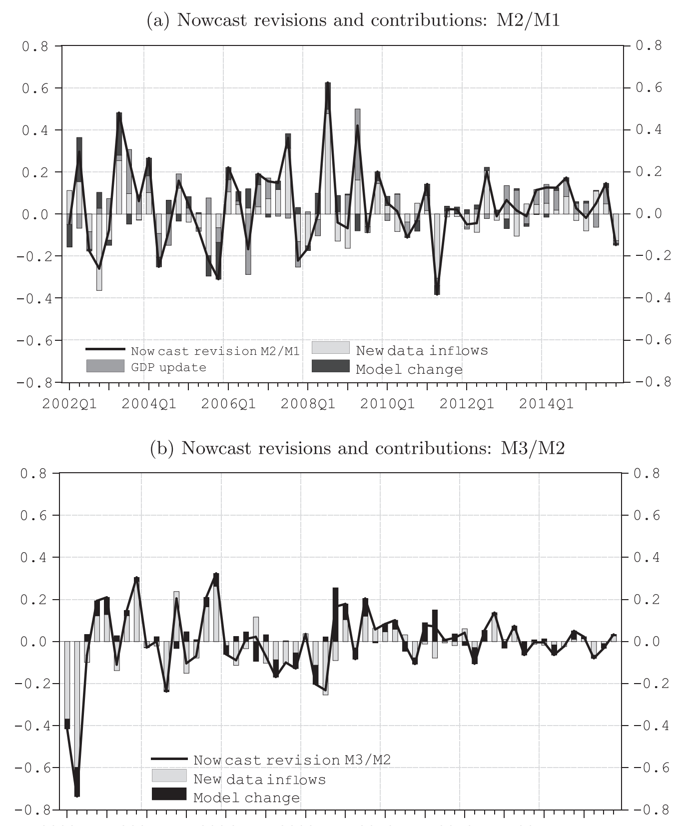

Fig. 3. Contributions to nowcast revisions (Q1 2002–Q4 2015), percentage points.

MSFE loss functions and compared with critical values from the Student's *t* distribution with ($T_{oos}-1$) degrees of freedom, as suggested by Harvey et al. (1997).[10]

6.1. The RTV-AR(p) model

Following the practice in the forecasting literature, we compare our model to a simple RTV-AR(p) model (Clements and Galvão, 2013), where the optimal number of autoregressive terms (p) is selected by optimizing the BIC criterion. Results are reported in Panel A of Table 3 and point to a large and statistically significant predictive gain for the MIBA model compared to the AR alternative: up to 30–40% over the full evaluation window, and up to 50% over more recent periods. These

[10] In some cases, the models may be nested, leading to a degenerate distribution of the DMW statistic (Clark and McCracken, 2001, 2005), so that the critical values tabulated by McCracken (2007) would be more appropriate for inference. However, as suggested by Ferrara et al. (2015), using standard critical values (which are more conservative than those reported by McCracken, 2007) represents a reasonable strategy in a context of limited number of out-of-sample observations, such as in the present study. Here we follow this approach, but we check whether the DMW test results are consistent with the output of the testing procedure suggested by Clark and West (2007, CW hereafter), which deals properly with the issue of nested models (only for the MSFE loss function). We also checked the robustness of our real-time out-of-sample results under a rolling-window estimation scheme, and we implemented the Giacomini and White (2006) test for either unconditional or conditional EPA between the benchmark and the alternative models. Results (not reported, but available upon request from the authors) are broadly in line

(footnote continued)
with those reported in Table 3, although the hypothesis of conditional EPA (where the test function includes one lag of the loss differential) can be rejected somewhat less frequently than the unconditional null.

Table 3
Benchmarking the new MIBA model.

	Q1 2002–Q4 2015		Q2 2007–Q4 2015		Q2 2009–Q4 2015	
Equations	MAFE	RMSFE	MAFE	RMSFE	MAFE	RMSFE
Panel A. RTV-AR(p) model						
M1	**0.72**	**0.67**	**0.65**	**0.62**	**0.58**	**0.59**
M2	**0.63**	**0.58**	**0.52**	**0.48**	**0.46**	**0.49**
M3	**0.67**	**0.62**	**0.55**	**0.53**	**0.50**	**0.48**
Panel B. Previous MIBA model						
M3	0.90	0.99	**0.78**	0.91	**0.74**	**0.74**
Panel C. New MIBA model with fully-automatic selection						
M1	**0.87**	**0.89**	**0.75**	**0.80**	**0.73**	**0.76**
M2	0.91	0.90	**0.74**	**0.73**	**0.75**	**0.75**
M3	**0.82**	**0.84**	**0.69**	**0.76**	**0.70**	**0.69**
Panel D. New MIBA model augmented with hard data						
M3	1.00	*1.11*	0.99	*1.18*	0.90	0.94
Panel E. MIDAS regressions						
M1	0.88	0.90	**0.82**	0.86	**0.73**	**0.68**
M2	**0.87**	**0.87**	**0.80**	**0.82**	**0.80**	**0.81**
M3	**0.71**	**0.72**	**0.63**	**0.65**	**0.67**	**0.67**
Panel F. Consensus Forecasts						
M3	**0.78**	**0.82**	**0.67**	**0.74**	**0.66**	**0.59**

Notes: Relative MAFE and RMSFE (<1 means that the new MIBA outperforms the alternative model). Bold values denote rejection of the null hypothesis of equal predictive accuracy at 10% level according to the one-sided t-statistic version of the DMW test or the CW test, the latter in case of nested models. Values in italic indicate that the alternative model significantly outperforms the benchmark. For Panel D, the sample of predictions starts in Q1 2005.

findings illustrate the crucial role played by survey data in our nowcasting equations compared to simple autoregressive specifications.

6.2. The previous version of the MIBA model

Next, the new MIBA model is compared to its main challenger, i.e. the previous version of the model. The latter consisted of three auxiliary mixed-frequency factor models, each including a lag of GDP, the first factor extracted from balances of opinion on the manufacturing sector, and, respectively, the third factor extracted from survey opinions on the manufacturing sector (first equation), the second factor extracted from survey opinions on the sub-sector "manufacturing of electric, electronic equipment and machines" (second equation), and the "changes in activity" balance of opinion from the monthly business survey on services (third equation). GDP nowcasts were then computed as a simple combination of the predictions obtained from these three equations using equal weights. Several "bridge" methods have been implemented overtime in the previous version of the MIBA model to deal with the ragged-edge issue (extrapolation using autoregressive models, simple average of the observations available over the quarter, and moving average over a window of the last three observations). To simplify the comparison exercise, we only focus on nowcasts stemming from the M3 equations, because the underlying specifications are not affected by partial information. Further, the previous MIBA model was consistent with the standard EOS approach. Hence, in order to replicate the real-time conditions of the forecaster, we use the GDP vintages actually available at the time of each nowcasting exercise to estimate model parameters and to compute the nowcasts.

Results are presented in Panel B of Table 3. According to MAFE, the new MIBA model is more accurate than its previous version by about 10% over the whole evaluation period, although the EPA hypothesis cannot be rejected. Predictive gains increase substantially over more recent periods (20–25%), and appear statistically significant. According to RMSFE, substantial predictive gains arise only over the latest evaluation period (not covering the Great Recession episode). Overall, we show that the new MIBA model can provide a reasonable nowcasting performance compared to its previous version, which satisfies one of the main conditions set by the present study.

6.3. The new MIBA model with fully-automatic selection

The effect of the model selection approach described in Section 3.2 on the nowcasting performance of the MIBA model is quantified by evaluating the predictive accuracy of a model specified through a fully-automatic approach. For this aim, we perform model selection by implementing the *Autometrics* algorithm, but we do not proceed with the sequential adjustment. In other words, we exclude the intervention of the forecaster on the automatic model selection provided by the algorithm.

Results, reported in Panel C of Table 3, suggest that the effect of the judgment-driven adjustments tends overall towards a significant outperformance of the MIBA model compared to the automatically selected alternative. Over the whole evaluation period, the predictive gain is about 10% for M1 and M2, but it increases to about 20% for M3. According to the tests for the EPA hypothesis, the latter is also statistically different from zero. Further, the gain (and its statistical significance) improves (up to 30%) when more recent evaluation periods are considered. These findings overall suggest that sensible judgment-driven adjustments in model selection may improve the performance of automatically selected specifications.

6.4. The MIBA model augmented with hard data

As stressed in the Introduction, one particular feature of the MIBA model is that it *must* be based exclusively on survey data collected by the Banque de France. Hence, no additional external predictors are allowed to enter the information pool available to the model builder. However, as suggested by Banbura and Rünstler (2011), while survey data play an important role, hard data are still found to convey relevant information when predicting GDP. It is hence worth asking what would be the predictive gain of the MIBA model if hard data were allowed to be used by the forecaster. We hence compare our model to a pseudo-MIBA model augmented with hard data indicators, such as quarter-on-quarter growth rates of total IPI, manufacturing IPI, construction index, households' consumption of goods, and energy/electricity production and consumption. However, publication lags for these series imply that only partial information is available to the forecaster when computing nowcasts. For instance, IPI is released with a lag of about 40 days, meaning that only the first monthly observation is available for nowcasting purposes, while the remaining information can be used for backcasting GDP. Here we address this issue by computing the quarter-on-quarter growth rate assuming that the missing monthly observations have an expected zero monthly growth rate. For instance, when only the first monthly observation ($z_{t-2/3}$) is available, we compute the quarter-on-quarter growth rate $\bar{z}_t^{(qoq)} = \left(z_{t-2/3} / 3^{-1} \sum_{j=4}^{6} z_{t-(j-1)/3} \right) - 1$, while when the first two monthly observations are available, the numerator is replaced with $\frac{1}{3} z_{t-2/3} + \frac{2}{3} z_{t-1/3}$.[11] Model selection is carried out by implementing the

[11] This rough approach, known by business analysts as *carry-over*, has the advantage of being easy to implement. Further, preliminary analysis (not reported) suggested that nowcasting results are quantitatively similar to alternative solutions based on bridge models, which use survey data to predict the missing monthly information of hard data.

Autometrics algorithm over the whole set of available indicators (survey variables and hard data). The selected specifications are very similar to those of the MIBA model, although not exactly the same, and they additionally include the manufacturing IPI. For this variable, which is usually subject to substantial revisions, we dispose of a real-time database spanning from the Q1 2005 vintage onwards. Given the limited number of available vintages, we cannot implement a pure RTV approach, but we can still take advantage of the real-time structure of the dataset to replicate the actual conditions of the forecaster using a mixed RTV-EOS strategy.

Results for the M3 equation, i.e. the only equation for which comparison is possible due to publication lags in the IPI, are reported in Panel D of Table 3. The findings suggest that the MIBA model is outperformed by the competing model over the whole evaluation period: the predictive gain is large and statistically significant according to RMSFE (although negligible according to MAFE), and it tends to increase in most recent years. Hence, results strongly suggest that including hard data can provide substantial nowcasting improvement. However, it is worth noting that the predictive gain disappears when the post-Great Recession sub-period is considered, suggesting that part of the superior performance of the alternative model may be related to a better accuracy during the quarters covering the crisis.

6.5. MIDAS regressions

Multivariate MIDAS regressions are specified and estimated over the set of monthly survey data using the (normalized) exponential Almon lag aggregation function (see, for instance, Lahiri and Monokroussos, 2013, and Ferrara and Marsilli, 2013):

$$y_t^{t+1} = \beta_0 + \sum_{j=1}^{p} \beta_j y_{t-j}^t + \sum_{s=1}^{w} \delta_s B_s(L^{1/3}, \boldsymbol{\theta}_s) x_{s,t} + \epsilon_t, \tag{3}$$

where $B_s(L^{1/3}, \boldsymbol{\theta}_s) = \sum_{c=h}^{C} b_s(c, \boldsymbol{\theta}_s) L^{(c-1)/3}$ and $b_s(c, \boldsymbol{\theta}_s) = \frac{\exp(\theta_{1,s}c + \theta_{2,s}c^2)}{\sum_{c=h}^{C} \exp(\theta_{1,s}c + \theta_{2,s}c^2)}$, with the monthly lag operator $L^{c/3}x_t = x_{t-c/3}$, and $\boldsymbol{\theta}_s = (\theta_{1,s}, \theta_{2,s})'$. Model selection (i.e. the choice of the optimal set of predictors and the lag structure) is carried out by optimizing the BIC criterion. Hence, we let $p^* \in (0, \ldots, p_{\max})$, $w^* \in (1, \ldots, w_{\max})$, and $C^* \in (6, 9, 12)$, with $p_{\max} = w_{\max} = 4$ to avoid over-parameterization.

Results, reported in Panel E of Table 3, suggest that the MIBA model broadly outperforms the alternative MIDAS specifications. Over the whole evaluation period, predictive gains range between 10-30%. Further, M2 and M3 equations provide a nowcasting accuracy statistically different from that of the MIDAS models. Over more recent periods, the predictive gain tends to increase and the rejection of the EPA hypothesis tends to strengthen.

6.6. Alternative professional forecasters

Finally, we compare the out-of-sample performance of the new MIBA model to the performance of a pool of professional forecasters (mainly commercial and investment banks, financial institutions, and consulting companies) surveyed by Consensus Economics Inc. in its Consensus Forecasts publications. Quarterly average predictions of GDP (the *consensus* among the pool of forecasts) are available on a year-on-year basis and are updated once a quarter, in the publication released in March, June, September and December. The analysis is carried out by first transforming these predictions into quarter-on-quarter observations using the GDP vintage actually available at the time of each publication release, and then by comparing the resulting series to predictions stemming from our M3 equation.

Results are reported in Panel F of Table 3 and suggest that the MIBA model broadly outperforms the Consensus Forecasts over the whole evaluation period and the two sub-periods. The predictive gain is about 20% in the former and up to 30-40% in the latter, and the EPA hypothesis can be strongly rejected overall.

7. Concluding remarks

In this study we presented the new model used by the Banque de France to nowcast French GDP. As in the previous versions, the model is compelled to rely exclusively on data from the monthly business survey on industry and services produced by the Banque de France itself. Several innovations were introduced in this new model. First, the new MIBA model is no longer based on factors extracted from the survey on industry, but rather on balances of opinion from this survey. Second, the GDP measure targeted by the nowcasting model is redefined to match initial announcements of GDP, rather than final (revised) announcements. Third, mixed-frequency and ragged-edge issues are addressed through the “blocking” approach.

Model selection was carried out using the General-to-Specific approach of the *Autometrics* algorithm, providing different nowcasting models for each forecast date. For the first forecast horizon, involving data available up to the first month of the quarter to be nowcast, the model is a mix of information on past and expected activity, the latter outweighing the former. For the second and third forecast horizons, involving data available respectively up to the second and third month of the quarter to be nowcast, forward-looking information is progressively discarded. It is worth noting that balances of opinion on services do not enter the selected equations, as they seem to be more suited for nowcasting final, rather than initial, announcements of GDP. With respect to the nowcasting performance of the new MIBA model, out-of-sample evaluation was carried out over the period Q1 2002–Q4 2015 and pointed to a good predictive accuracy. When compared to various alternative specifications, such as the previous version of the model and MIDAS regressions, both evaluation criteria and test results for equal predictive accuracy pointed overall to a substantial outperformance for the new MIBA model. These findings are sometimes more clear-cut when more recent years are considered. Conversely, results suggest that a model augmented with hard data is superior to the new MIBA model, but this evidence tends to disappear when recent years, that exclude the Great Recession episode, are considered.

The results presented in this study can be additionally challenged in several ways. For instance, Bessec (2013) and Girardi et al. (in press) show that factor models with targeted predictors can provide substantial gains in terms of predictive accuracy of GDP. Further, Vlavonou and Gordon (in press) show that using a dynamic factor model to estimate unobserved monthly US GDP represents a promising new approach. Finally, our study does not consider forecast combinations, nor an evaluation based on density forecasts. These issues will be examined in further research.

Acknowledgements

We are indebted to Véronique Brunhes-Lesage for valuable research assistance. We wish to thank Pierre Sicsic, Marie Diron, Thomas Ferrière, and participants at Banque de France seminars for helpful comments. We also thank the Editor, the Associate Editor, and two anonymous referees for very useful suggestions. The usual disclaimer applies. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Banque de France.

Appendix

Decomposing the contribution to nowcast revisions

This proof relies on the notation introduced in Section 2.2 and follows in part from Dubois and Michaux (2006). Compared to Section 2.2, we neglect the issue of data revisions for ease of analysis.

Suppose we have the following two consecutive simple nowcasting equations:

$$y_t = \beta_0^{(1)} + \sum_{i=1}^{p} \beta_i^{(1)} y_{t-i} + \sum_{s=1}^{4} \gamma_{s,3}^{(1)} L^{(3-1)/3} x_{s,t} + \epsilon_t^{(1)} \tag{A1a}$$

$$y_t = \beta_0^{(2)} + \sum_{i=1}^{p} \beta_i^{(2)} y_{t-i} + \sum_{s=1}^{2} \gamma_{s,2}^{(2)} L^{(2-1)/3} x_{s,t} + \sum_{s=3}^{4} \gamma_{s,3}^{(2)} L^{(3-1)/3} x_{s,t} + \epsilon_t^{(2)} \tag{A1b}$$

where y_t is a quarterly variable, $x_{s,t}$ are monthly variables, and $\gamma_s(L^{1/3})$ are linear lag polynomials, with $L^{(j-1)/3} x_{s,t} = x_{s,t-(j-1)/3}$. Let us denote $\mathbf{z}_t = \left(1, y_{t-1}, \ldots, y_{t-p}, x_{3,t-2/3}, x_{4,t-2/3}\right)'$ the vector of variables common to both equations, $\mathbf{x}_t^{(1)} = (x_{1,t-2/3}, x_{2,t-2/3})'$ the vector of variables entering the first equation only, and $\mathbf{x}_t^{(2)} = (x_{1,t-1/3}, x_{2,t-1/3})'$ the vector of variables entering the second equation only. Let $\hat{y}_T^{(1)}$ be the nowcast of y_T provided by the first equation and $\hat{y}_T^{(2)}$ the nowcast provided by the second equation, with both equations estimated using data up to period $t = T - 1$. If $\hat{y}_T^{(2)} - \hat{y}_T^{(1)} \neq 0$, nowcasts are revised across the equations, and the revision can be explained by both a change in the model, i.e. the absence of $\mathbf{x}_t^{(1)}$ in (A1b), and the inflow of new information, i.e. the updated information represented by $\mathbf{x}_t^{(2)}$ in (A1b).

In order to disentangle these two factors, let us run the following auxiliary regressions of the variables entering the second equation only on the common variables and the variables entering the first equation only:

$$x_{s,t-\frac{1}{3}} = \mathbf{a}'_s \mathbf{z}_t + \mathbf{b}'_s \mathbf{x}_t^{(1)} + u_{s,t-\frac{1}{3}} \tag{A2}$$

for s=1,2. From the Frisch-Waugh-Lovell theorem and the properties of OLS, the residuals from the orthogonal projection of the $\mathbf{x}_t^{(2)}$ components of regression (A1b) on $\mathbf{z}_t$ and $\mathbf{x}_t^{(1)}$ can be interpreted as the non-redundant information provided by the variables $x_{1,t-1/3}$ and $x_{2,t-1/3}$ (denoted $x_{1,t-1/3}^{\perp}$ and $x_{2,t-1/3}^{\perp}$) with respect to common variables and variables belonging exclusively to the regression (A1b):

$$x_{s,t-\frac{1}{3}}^{\perp} = \hat{u}_{s,t-\frac{1}{3}} = x_{s,t-\frac{1}{3}} - \hat{x}_{s,t-\frac{1}{3}} \tag{A3}$$

for s=1,2. By construction, $\mathbf{x}_t^{(2)\perp} = (x_{1,t-1/3}^{\perp}, x_{2,t-1/3}^{\perp})'$ is orthogonal to $\mathbf{z}_t$ and $\mathbf{x}_t^{(1)}$. Further, $\hat{\epsilon}_t^{(2)}$ is also orthogonal to $\mathbf{z}_t$ and $\mathbf{x}_t^{(1)}$, the former by construction and the latter because otherwise $\mathbf{x}_t^{(1)}$ should be included in regression (A1b). Let us rewrite regression (A1b), replacing $\mathbf{x}_t^{(2)}$ with $\hat{\mathbf{x}}_t^{(2)} = (\hat{x}_{1,t-1/3}, \hat{x}_{2,t-1/3})'$. We have that:

$$y_t - \hat{\boldsymbol{\beta}}^{(2)\prime} \mathbf{z}_t - \hat{\boldsymbol{\gamma}}^{(2)\prime} \hat{\mathbf{x}}_t^{(2)} = y_t - \hat{\boldsymbol{\beta}}^{(2)\prime} \mathbf{z}_t - \hat{\boldsymbol{\gamma}}^{(2)\prime} \mathbf{x}_t^{(2)} + \hat{\boldsymbol{\gamma}}^{(2)\prime} (\mathbf{x}_t^{(2)} - \hat{\mathbf{x}}_t^{(2)}) = \hat{\epsilon}_t^{(2)} + \hat{\boldsymbol{\gamma}}^{(2)\prime} \mathbf{x}_t^{(2)\perp} \tag{A4}$$

where $\hat{\boldsymbol{\beta}}^{(2)} = \left(\hat{\beta}_0^{(2)}, \hat{\beta}_1^{(2)}, \ldots, \hat{\beta}_p^{(2)}, \hat{\gamma}_{3,3}^{(2)}, \hat{\gamma}_{4,3}^{(2)}\right)'$ and $\hat{\boldsymbol{\gamma}}^{(2)} = (\hat{\gamma}_{1,2}^{(2)}, \hat{\gamma}_{2,2}^{(2)})'$. Using the orthogonality conditions for $\hat{\epsilon}_t^{(2)}$ and $\mathbf{x}_t^{(2)\perp}$ with respect to $\mathbf{z}_t$ and $\mathbf{x}_t^{(1)}$, we have that $\hat{\epsilon}_t^{(2)} + \hat{\boldsymbol{\gamma}}^{(2)\prime} \mathbf{x}_t^{(2)\perp}$ is also orthogonal to $\mathbf{z}_t$ and $\mathbf{x}_t^{(1)}$. Since $\hat{\epsilon}_t^{(1)}$ is orthogonal (by construction) to $\mathbf{z}_t$ and $\mathbf{x}_t^{(1)}$, and from (A3) $\hat{\boldsymbol{\beta}}^{(2)\prime} \mathbf{z}_t - \hat{\boldsymbol{\gamma}}^{(2)\prime} \hat{\mathbf{x}}_t^{(2)}$ is a linear combination of $\mathbf{z}_t$ and $\mathbf{x}_t^{(1)}$, the following out-of-sample approximation holds:

$$\hat{y}_T^{(1)} \approx \hat{\boldsymbol{\beta}}^{(2)\prime} \mathbf{z}_T + \hat{\boldsymbol{\gamma}}^{(2)\prime} \hat{\mathbf{x}}_T^{(2)} \approx \hat{\boldsymbol{\beta}}^{(2)\prime} \mathbf{z}_T + \hat{\boldsymbol{\gamma}}^{(2)\prime} (\mathbf{x}_T^{(2)} - \mathbf{x}_T^{(2)\perp}) \tag{A5}$$

where $\mathbf{z}_T = \left(1, y_{T-1}, \ldots, y_{T-p}, x_{3,T-2/3}, x_{4,T-2/3}\right)'$ and $\mathbf{x}_T^{(2)\perp} = (x_{1,T-1/3}^{\perp}, x_{2,T-1/3}^{\perp})'$. Hence, since $\hat{y}_T^{(2)} = \hat{\boldsymbol{\beta}}^{(2)\prime} \mathbf{z}_T + \hat{\boldsymbol{\gamma}}^{(2)\prime} \mathbf{x}_T^{(2)}$, nowcast revisions can be approximated by the following:

$$\hat{y}_T^{(2)} - \hat{y}_T^{(1)} \approx \hat{\boldsymbol{\gamma}}^{(2)\prime} \mathbf{x}_T^{(2)} - \hat{\boldsymbol{\gamma}}^{(2)\prime} (\mathbf{x}_T^{(2)} - \mathbf{x}_T^{(2)\perp}) \approx \hat{\boldsymbol{\gamma}}^{(2)\prime} \mathbf{x}_T^{(2)\perp} \tag{A6}$$

This approximation represents the contribution of the inflow of new information to nowcast revisions (the non-redundant information conveyed by the variables belonging to the second equation only, weighted by their estimated coefficients), while the residual unexplained revisions can be attributed to the change in the model. .

Now, suppose that the value for y_{T-1} in $\mathbf{z}_T$ is not observed when nowcasting with Eq. (A1a), due for instance to publication lags. This also implies that Eq. (A1a) can be estimated using data only up to period $t = T - 2$, but we assume that coefficients $\hat{\boldsymbol{\beta}}^{(1)} = \left(\hat{\beta}_0^{(1)}, \hat{\beta}_1^{(1)}, \ldots, \hat{\beta}_p^{(1)}, \hat{\gamma}_{3,3}^{(1)}, \hat{\gamma}_{4,3}^{(1)}\right)'$ and $\hat{\boldsymbol{\gamma}}^{(1)} = (\hat{\gamma}_{1,3}^{(1)}, \hat{\gamma}_{2,3}^{(1)})'$ are not sensitive to the estimation sample. Suppose that an estimate of y_{T-1}, $\hat{y}_{T-1}$, is available (e.g., from the previous nowcast), and that this estimate is plugged-in Eq. (A1a) to nowcast y_T. This implies that nowcast revisions can be additionally explained by the update of $\hat{y}_{T-1}$, from an estimate to its actual value, between the first and the second equation. This can be seen by replacing $\mathbf{z}_t$ with $\tilde{\mathbf{z}}_t = \left(1, \hat{y}_{t-1}, \ldots, y_{t-p}, x_{3,t-2/3}, x_{4,t-2/3}\right)'$ and adding an extra term, $\kappa_t = y_{t-1} - \hat{y}_{t-1}$, to the expression for the conditional expectation of $\hat{y}_T^{(2)}$. Indeed, from Eqs. (A1a) and (A1b), conditional expectations can be written as:

$$\begin{aligned} \hat{y}_T^{(1)} &= \hat{\boldsymbol{\beta}}^{(1)\prime} \tilde{\mathbf{z}}_T + \hat{\boldsymbol{\gamma}}^{(1)\prime} \mathbf{x}_T^{(1)} \\ \hat{y}_T^{(2)} &= \hat{\boldsymbol{\beta}}^{(2)\prime} \tilde{\mathbf{z}}_T + \hat{\boldsymbol{\gamma}}^{(2)\prime} \mathbf{x}_T^{(2)} + \hat{\beta}_1^{(2)} \kappa_T \end{aligned}$$

where $\tilde{\mathbf{z}}_T = \left(1, \hat{y}_{T-1}, \ldots, y_{T-p}, x_{3,T-2/3}, x_{4,T-2/3}\right)'$ and $\kappa_T = y_{T-1} - \hat{y}_{T-1}$. Following the results presented above, we have that forecast revisions can be now approximated by the following:

$$\begin{aligned} \hat{y}_T^{(2)} - \hat{y}_T^{(1)} &\approx \hat{\boldsymbol{\gamma}}^{(2)\prime}\mathbf{x}_T^{(2)} - \hat{\boldsymbol{\gamma}}^{(2)\prime}(\mathbf{x}_T^{(2)} - \mathbf{x}_T^{(2)\perp}) + \hat{\beta}_1^{(2)} \\ \kappa_T &\approx \hat{\boldsymbol{\gamma}}^{(2)\prime}\mathbf{x}_T^{(2)\perp} + \hat{\beta}_1^{(2)}\kappa_T \end{aligned} \tag{A7}$$

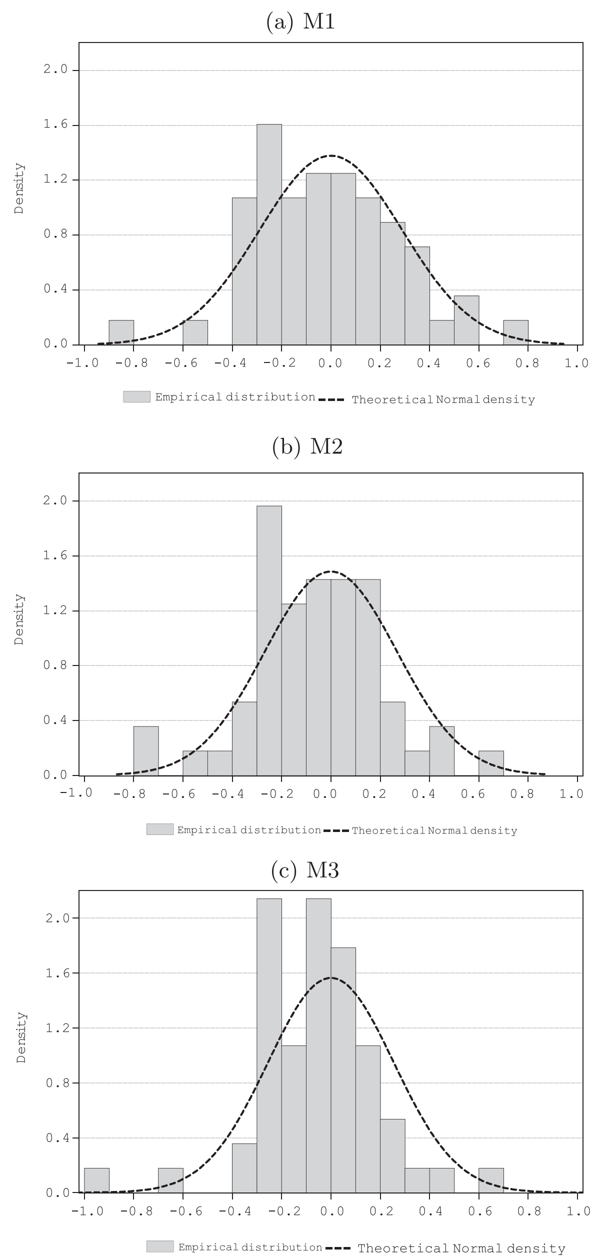

Fig. A1. Distribution of prediction errors (Q1 2002–Q4 2015).

Table A1
Balances of opinion on manufacturing sector and market services.

Balance of opinion	Sector	Question	Reference period
EVPRO	Manufacturing	Changes in production	M/M-1
EVLIV	Manufacturing	Changes in deliveries	M/M-1
EVCOM	Manufacturing	Changes in overall orders	M/M-1
EVCOME	Manufacturing	Changes in foreign orders	M/M-1
EVPRMP	Manufacturing	Changes in commodity prices	M/M-1

(continued on next page)

Table A1 *(continued)*

Balance of opinion	Sector	Question	Reference period
EVPRPF	Manufacturing	Changes in prices of finished goods	M/M-1
EVSTPF	Manufacturing	Changes in inventories of finished goods	M/M-1
ETCC	Manufacturing	Order books	M/“norm”
STPF	Manufacturing	Inventories of finished goods	M/“norm”
STMP	Manufacturing	Inventories of commodities	M/“norm”
CSEMA	Manufacturing	Weekly order levels	M/M-1
TUC	Manufacturing	Average capacity utilisation rate	M/M-1
PREVPRO	Manufacturing	Expected changes in production	M+1/M
PREVSTPF	Manufacturing	Expected changes in inventories of finished goods	M+1/M
EVACT	Services	Changes in activity	M/M-1
EVPRIX	Services	Changes in prices	M/M-1
EVEFF	Services	Changes in staff levels	M/M-1
NIVTRES	Services	Levels of cash flows	M
PREVACT	Services	Expected changes in activity	M+1/M
PREVPRIX	Services	Expected changes in prices	M+1/M
PREVEFF	Services	Expected changes in staff levels	M+1/M

Notes: M denotes the current month. M/M-1 denotes the current month compared to the previous month. M+1/M denotes expectations over the next month compared to the current month. M/“norm” denotes the current month compared to a normal level. Four additional balances of opinion on the manufacturing sector enter the survey, but have shorter historical records. Survey data on the market services sector are collected over ten sub-sectors of activity: hotels, temporary employment, computer engineering, technical engineering, car rental, business and management counseling services, agencies, advertising, cleaning services, car repair and road freight transport.

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