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A comparison of mixed frequency approaches for nowcasting Euro area macroeconomic aggregates

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ABSTRACT

In this paper, we focus on the different methods which have been proposed in the literature to date for dealing with mixed-frequency and ragged-edge datasets: bridge equations, mixed-data sampling (MIDAS), and mixed-frequency VAR (MF-VAR) models. We discuss their performances for nowcasting the quarterly growth rate of the Euro area GDP and its components, using a very large set of monthly indicators. We investigate the behaviors of single indicator models, forecast combinations and factor models, in a pseudo real-time framework. MIDAS with an AR component performs quite well, and outperforms MF-VAR at most horizons. Bridge equations perform well overall. Forecast pooling is superior to most of the single indicator models overall. Pooling information using factor models gives even better results. The best results are obtained for the components for which more economically related monthly indicators are available. Nowcasts of GDP components can then be combined to obtain nowcasts for the total GDP growth.

1. Introduction

In recent times, forecast models that take into account the information in unbalanced datasets have attracted substantial amounts of attention. Policy-makers, in particular, need to assess the current state of the economy in real-time, when complete information is not available.

In real-time, the unbalancedness of datasets arises as a result of two main features: the different sampling frequencies at which the indicators are available, and the so-called "ragged-edge" problem, namely publication delays of indicators, which cause missing values of some of the variables at the end of the sample, see Wallis (1986). As an example, one of the key indicators of macroeconomic activity, the Gross Domestic Product (GDP), is released quarterly and with a considerable publication lag, while various leading and coincident indicators are available in a more timely fashion and at a monthly or even higher frequency.

In this paper, we focus on different classes of models which deal with unbalanced datasets. In particular, we concentrate on three main streams in the literature: bridge models, the state space approach and the MIDAS approach. Bridge equations are one of the most used techniques, since they link monthly and quarterly variables, choosing the regressors because of their timely information content (see e.g. Baffigi, Golinelli, & Parigi, 2004). State space approaches aim to capture the joint dynamics of indicators at different frequencies. Two main models are developed within this framework: the mixed-frequency VAR and factor models. In both cases, the use of the Kalman filter allows a monthly estimate of the quarterly series to be obtained. Mariano and Murasawa (2010) set what they call

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a mixed-frequency VAR (MF-VAR from now on), i.e., they introduce a VAR model for partially latent time series and cast it in state space form.[1] Among the state space approaches we can also list the mixed-frequency factor models that are employed, for example, to extract an unobserved state of the economy and create a new coincident indicator, or to forecast and nowcast GDP, see for example Camacho and Perez-Quiros (2010), who construct a coincident indicator of the Euro area economy, the so-called Euro-STING indicator, which evolves according to the Euro area dynamics and is based on an extension of the dynamic factor model described by Mariano and Murasawa (2003).[2] Recent studies in the literature (Camacho, Perez-Quiros, & Poncela, 2012a,b) have extended the Euro-STING even further to incorporate Markov-switching dynamics. The third approach, the MIDAS method, is based on a univariate reduced form regression, which uses highly parsimonious lag polynomials to exploit the content in the higher-frequency explanatory variable and provide a high-frequency update of the quarterly frequency variable (see for example Ghysels, Santa-Clara, & Valkanov, 2004, for financial applications; and Clements & Galvao, 2008, and Guerin & Marcellino, 2013, for macroeconomic applications). Recently, these factor and MIDAS approaches have been merged in the Factor-MIDAS model, augmenting the MIDAS regressions with factors extracted from a large, high frequency dataset (see Marcellino & Schumacher, 2010).

All of these approaches tackle data at different frequencies and with publication delays, but at the same time they display different characteristics, which makes it difficult to rank them only on the basis of theoretical considerations a priori. Therefore, we compare them in an extensive and detailed empirical application.

As an original contribution to the literature, we focus on nowcasting the quarterly growth rate of Euro area GDP components, disaggregating GDP from the production and expenditure side. In fact, following an output approach, the GDP can be defined as the sum of the gross value added of the different industries (plus taxes minus subsidies). We identify and nowcast six components: agriculture, industry, construction, trade, financial services and others (following the Eurostat classification). In addition, following an expenditure approach, the GDP can be seen as the sum of final uses of goods and services, plus the external balance. We therefore distinguish among consumption, gross fixed capital formation, exports and imports.

We use a very large set of monthly indicators (around 150 monthly series), with a wide range of forecasting methods. In order to compare the different approaches, we both investigate the behaviors of individual indicator models and combine the forecasts within each class of models. We conduct the analysis recursively in a pseudo real-time framework, taking the ragged-edge structure of the dataset into account, and assess the nowcasting performances of the models by comparing the resulting mean-squared errors (MSE). Specifically, we begin by investigating the performances of a large number of single indicator models. Then, since all of the approaches can be subject to misspecification issues, related to points such as indicator selection or the number of lags, for example, we propose forecast pooling as a way of dealing with this model uncertainty (see Timmermann, 2006, for an extensive review of forecast pooling approaches). We consider the median as a simple weighting scheme, and discuss whether it provides results which are robust to misspecification and parameter instability. We also consider the use of factor models, and in particular of the recent Factor-MIDAS, as a way of pooling information rather than forecasts.

Finally, we look at the usefulness of the disaggregated information contained in the components of GDP for nowcasting the total GDP growth. In order to do this, we aggregate the nowcasts obtained from the different components and compare them with the nowcasts obtained by considering only the total GDP aggregate. When using a simple constant weighting scheme, we can see that looking at disaggregate information can provide some improvements.

We anticipate some of the results here. First, there is no clear evidence of which approach to handling mixed-frequency data with ragged edges is the best. A general finding is that, when looking at single indicator models, MF-VAR does not show any particular improvement in terms of MSE, while AR-MIDAS and bridge equations generally obtain better nowcasts. Looking at the pooling results, there is evidence that the bridge and AR-MIDAS approaches perform better, depending on which component we are focusing on. Even better results are obtained by pooling information using factor models, rather than pooling forecasts. Standard quarterly factor models can outperform the AR benchmark, for most of the components. Not surprisingly, bigger gains are obtained for the components for which more relevant monthly indicators are available in the dataset. Finally, looking at the components of GDP can also help in nowcasting the aggregate measure.

The paper proceeds as follows. Section 2 describes the data. Section 3 discusses model specification. Section 4 presents the results on nowcasting the quarterly Euro area GDP components, using single indicator models. Section 5 focuses on forecast pooling of the individual models. Section 6 looks at the results from factor models, which pool information from large numbers of time series, as distinct from what is done in Section 5, where the nowcasts of individual models are pooled. Section 7 combines the results of the components to obtain nowcasts for the Euro area GDP growth. Section 8 concludes.

[1] The estimation of MF-VAR models with Bayesian techniques has recently been been considered as an alternative framework in the literature. One of the earliest studies on this was the paper by Chiu, Eraker, Foerster, Kim, and Seoane (2011). In this paper, the authors develop a Gibbs sampling approach for estimating a VAR with mixed and irregularly sampled data. Another recent study is that by Schorfheide and Song (2011). The authors represent the MF-VAR as a state space model, and use MCMC methods to conduct Bayesian inference for model parameters and unobserved monthly variables.

[2] Aruoba and Diebold (2010) provide another significant example of an extension of the mixed-frequency factor model proposed by Mariano and Murasawa (2003), focusing on the US economy.

2. Data

The dataset contains Euro area quarterly and monthly series taken from the Eurostat dataset of Principal European Economic Indicators (PEEI). We consider a fixed country composition of the Euro area, as it was in 2009 at the end of the sample, with 16 countries. We collect the quarterly GDP from 1996Q1 until 2009Q2, both at the aggregate level and disaggregated into branches of activity and expenditure components. We also collect around 150 macroeconomic monthly indicators from January 1996 to August 2009, including the consumer and producer price indexes by sector, industrial production and (deflated) turnover indexes by sector, car registrations, the new orders received index, business and consumer surveys with their components, sentiment indicators, unemployment indices, monetary aggregates, interest and exchange rates.[3] Besides providing a detailed overview of the economy, a large set of indicators is particularly useful in this context where there are several variables as forecast targets, since different indicators may have predictive power for each target. All of the series are seasonally adjusted. Details about the transformations and stock/flow nature of the data can be found in the Appendix.

The dataset is a final vintage dataset. However, we take one of the specific characteristics of macroeconomic data in real time into account, namely the ragged-edge structure of the dataset as a result of the series' different publication lags. The timing of data releases is more or less the same every month, and this allows us to replicate the same pattern of missing values at the end of each recursive sample. To give an indication of the ragged-edge structure of the dataset, we show the delays of the main series in the dataset in Table 1.[4]

As has been outlined in the recent literature, the use of pseudo real-time datasets, which replicate the differences in the availability of data, can lead to significant differences in results relative to the use of artificially balanced datasets, see Breitung and Schumacher (2008) and Giannone, Reichlin, and Small (2008), among others. Therefore, in our paper, we replicate the ragged-edge structure of the dataset which we observed at the time of download (31st August, 2009) in each of the recursive subsamples: for each series, we observe the number of missing values at the end, and impose the same number of missing observations at each recursion, so as to mimic the availability of data in real-time. To clarify, at the end of August 2009, for example, we have data on the CPI index and financial variables available until July 2009, but data on unemployment and industrial production only until June 2009; i.e., while the former variables have a delay of one month, the latter become available with a delay of two months. Therefore, when we use a subsample from January 1996 to March 2009 in our recursive exercise, we only use the CPI index until February 2009 and unemployment until January 2009, in order to replicate the data availability we would have in real-time. Moreover, we impose a similar structure of publication delays on the quarterly variables, namely GDP and its components on the production and expenditure side. To do this, we take into account the fact that in the Euro area, GDP and the components into which it is broken down are available in the third month after the end of the quarter of interest; for example, the GDP figure for 2009Q1 becomes available in June 2009.

3. Model specification

The aim of the experiment is to evaluate the performances of the different methods which are available in the literature for dealing with unbalanced mixed-frequency datasets, when the number of indicators is very large.

We will take the aggregate Euro area GDP growth rate as an example here, but the same procedure is followed for each production and expenditure component. We first recursively estimate and then nowcast the GDP growth rate, with the first evaluation quarter fixed at 2003Q1 and the last at 2009Q1, for a total of 25 recursive evaluation samples. For each quarter, we compute three nowcasts, based on different information sets.[5] Each of these projections for every realization of the GDP growth rate in the evaluation sample is based on different information, that which is available at the point in time when the projection is computed. We therefore exploit the ragged-edge structure of the dataset and consider only the information which is available at that moment. As has already been stated in the description of the data, the GDP components in the Euro area are available with a delay of 65 days after the end of the quarter of interest.

In terms of notation, we denote the GDP growth as y_{t_q}, where $t_q = 1, 2, 3, \ldots, T_q^y$ is a quarterly time index and T_q^y is the final quarter for which GDP is available.[6] The GDP growth can also be expressed as a monthly variable with missing values, by setting $t_m = t_q, \ \forall t_m = 3t_q$, where t_m is the monthly time index. GDP growth is observable only in $t_m = 3, 6, 9, \ldots, T_m^y$, where $T_m^y = 3T_q^y$. Therefore, what we want to obtain is a nowcast of the economic activity one quarter ahead, or equivalently, $h_m = 3$ months ahead. We exploit monthly stationary indicators x_{t_m}, with $t_m = 1, 2, 3, \ldots, T_m^x$, where T_m^x is the final month for which the indicator is available. Monthly indicators are usually available earlier in the quarter than the GDP release, so we generally condition the nowcast on the information available up to month T_m^x, which includes GDP information up to T_q^y and indicator observations up to T_m^x, with $T_m^x \geq T_m^y = 3T_q^y$. The GDP growth forecast is indicated as $y_{T_m^y+h_m|T_m^x}$.

[3] 1996 is the first year for which data for the Euro area was provided by Eurostat for many important indicators, and in particular for the different measures of inflation. We therefore consider 1996 as the starting point for our dataset.

[4] In the Eurostat PEEI dataset, financial variables such as interest and exchange rates are only available with a one month delay, even though it would be possible to obtain them in a more timely manner from other sources.

[5] As an example, for 2005Q3, we have nowcasts computed in September 2005, August 2005 and July 2005.

[6] In the empirical application, y_{t_q} represents the quarterly growth rate of each component.

Table 1
Main publication lags.

Main releases	Publishing lag	Frequency
HICP	1 month	monthly
PPI	2 months	monthly
Industrial production	2 months	monthly
Industrial new orders	2 months	monthly
Turnover index	2 months	monthly
Hours worked	2 months	monthly
Car registrations	2 months	monthly
Retail trade	2 months	monthly
Construction output	2 months	monthly
Business survey	current month	monthly
Business climate indicator	current month	monthly
Consumer survey	current month	monthly
Money supply	1 month	monthly
Exchange rates (average)	1 month	monthly
Interest rates (average)	1 month	monthly
Stock exchange indexes (average)	1 month	monthly
Unemployment	2 months	monthly
GDP: disaggregation of sectorial value added	1 quarter	quarterly
GDP: disaggregation from expenditure side	1 quarter	quarterly

Notes: The publishing lags correspond to the numbers of missing observations at the end of the sample at the date of download.

3.1. The bridge model approach

One of the earliest econometric approaches in the presence of mixed-frequency data relies on the use of bridge equations, see e.g. Baffigi et al. (2004) and Diron (2008). Bridge equations are linear regressions that link ("bridge") high frequency variables, such as industrial production or retail sales, to low frequency ones, e.g., the quarterly real GDP growth, providing some estimates of current and short-term developments in advance of the release. The "bridge model" technique allows the computation of early estimates of the low-frequency variables by using high frequency indicators.

In our exercise, since the monthly indicators are usually only partially available over the projection period, the predictions of quarterly GDP growth are obtained in two steps. First, monthly indicators are forecast over the remainder of the quarter, on the basis of univariate time series models, and then aggregated to obtain their corresponding quarterly values. Second, the aggregated values are used as regressors in the bridge equation, which allows us to obtain forecasts of GDP growth.

Therefore, the bridge model to be estimated is

$$y_{t_q} = \alpha + \gamma y_{t_q-1} + \sum_{i=1}^{j} \beta_i(L) x_{it_q} + u_{t_q}, \tag{1}$$

where $\beta_i(L)$ is a lag polynomial of length k, and x_{it_q} are the selected monthly indicators aggregated to the quarterly frequency.

In order to forecast the missing observations of the monthly indicators, which are then aggregated to obtain a quarterly value of x_{it_q}, it is common practice to use autoregressive models, where the lag length is based on information criteria.

In our exercise, we use autoregressive models, where the lag length is chosen according to the BIC, with the maximum lag fixed to 12. The data are then aggregated using standard methods, according to the stock/flow nature of the variables, specifically averaging over one lower-frequency period for the stock variables and summing over the high-frequency indicators for the flow variables. Once the data have been aggregated, the number of lags of the indicators to be included in the bridge model is chosen according to the BIC, with a maximum lag of 4.

3.2. The MF-VAR approach

A second approach for dealing with mixed-frequency time series, which is well-established in the literature at the moment, is the one proposed by Zadrozny (1988) for estimating a VARMA model sampled at different frequencies directly. The approach treats all of the series as being generated at the highest frequency, but considers some of them as being unobserved. Those variables that are observed only at the low frequency are therefore considered as being missing periodically.

Following the notation of Mariano and Murasawa (2010), we consider the state space representation of a VAR model, treating quarterly series as monthly series with missing observations. The disaggregation of the quarterly GDP growth, y_{t_m}, into the unobserved month-on-month GDP growth, $y^*_{t_m}$, is based on the following aggregation equation:

$$\begin{aligned} y_{t_m} &= \frac{1}{3}\left(y^*_{t_m} + y^*_{t_m-1} + y^*_{t_m-2}\right) \\ &\quad + \frac{1}{3}\left(y^*_{t_m-1} + y^*_{t_m-2} + y^*_{t_m-3}\right) \\ &\quad + \frac{1}{3}\left(y^*_{t_m-2} + y^*_{t_m-3} + y^*_{t_m-4}\right) \\ &= \frac{1}{3}y^*_{t_m} + \frac{2}{3}y^*_{t_m-1} + y^*_{t_m-2} + \frac{2}{3}y^*_{t_m-3} + \frac{1}{3}y^*_{t_m-4}, \end{aligned} \tag{2}$$

where $t_m = 3, 6, 9, \ldots, T_m$, since GDP growth, y_{t_m}, is observed in the last month of each quarter, while $y^*_{t_m}$ is never observed.

This aggregation equation comes from the assumption that the quarterly GDP series (in log levels), Y_{t_m}, is the geometric mean of the latent monthly random sequence $Y^*_{t_m}, Y^*_{t_m-1}, Y^*_{t_m-2}$. Taking the three-period differences and defining $y_{t_m} = \Delta_3 Y_{t_m}$ and $y^*_{t_m} = \Delta Y^*_{t_m}$, we obtain Eq. (2).

For all t_m, let the latent month-on-month GDP growth $y^*_{t_m}$ and the corresponding monthly indicator x_{t_m} follow a bivariate VAR(p) process

$$\phi(L_m)\begin{pmatrix} y^*_{t_m} - \mu^*_y \\ x_{t_m} - \mu_x \end{pmatrix} = u_{t_m}, \tag{3}$$

where $u_{t_m} \sim N(0, \Sigma)$.

State space representation.

In our exercise, we determine the number of lags, p, according to the Bayesian Information Criterion (BIC), with a maximum lag order of $p = 4$ months.

With $p \leq 4$, and defining s_{t_m} and z_{t_m} as

$$s_{t_m} = \begin{pmatrix} z_{t_m} \\ \vdots \\ z_{t_m-4} \end{pmatrix} \quad \text{and} \quad z_{t_m} = \begin{pmatrix} y^*_{t_m} - \mu^*_y \\ x_{t_m} - \mu_x \end{pmatrix},$$

a state space representation of the MF-VAR is

$$s_{t_m} = F s_{t_m-1} + G v_{t_m} \tag{4}$$

$$\begin{pmatrix} y_{t_m} - \mu_y \\ x_{t_m} - \mu_x \end{pmatrix} = H s_{t_m}, \tag{5}$$

with $\mu_y = 3\mu^*_y$, and $v_{t_m} \sim N(0, I_2)$. The matrices are defined as

$$F = \begin{bmatrix} F_1 \\ F_2 \end{bmatrix}; \qquad F_1 = \begin{bmatrix} \phi_1 & \cdots & \phi_p & 0_{2\times 2(5-p)} \end{bmatrix}; \qquad F_2 = \begin{bmatrix} I_8 & 0_{8\times 2} \end{bmatrix}, \tag{6}$$

$$G = \begin{bmatrix} \Sigma^{1/2} \\ 0_{8\times 2} \end{bmatrix}; \qquad H = \begin{bmatrix} H_0 & \cdots & H_4 \end{bmatrix}, \qquad H_i = (i+1)\begin{bmatrix} 1/3 & 0 \\ 0 & 0 \end{bmatrix}. \tag{7}$$

Estimation and forecasting.

The state space representation of the mixed-frequency VAR model, described by Eqs. (4) and (5), can be estimated by maximum-likelihood, even in the presence of missing observations due to publication lags and the low-frequency nature of the GDP. However, when the number of parameters is large, the ML method can fail to converge.

We therefore implement a version of the EM algorithm which has been modified to allow for missing observations. Like Mariano and Murasawa (2010), we consider the missing values as realizations of some i.i.d. standard normal random variables, i.e.,

$$y^+_{t_m} = \begin{cases} y_{t_m} & \text{if } y_{t_m} \text{ is observable} \\ \zeta_{t_m} & \text{otherwise,} \end{cases} \tag{8}$$

where ζ_{t_m} is a draw from a standard normal distribution independent of the model parameters.

The measurement equation is modified accordingly in the first two months of each quarter, where the upper row of H is set to zero and a standard normal error term is added, so that the Kalman filter skips the random numbers. Since the realizations of the random numbers do not matter in practice, we replace the missing values with zeros.

We use the Kalman smoother to obtain forecasts of the economic activity. Although the GDP growth for particular months is not available, the smoother considers the monthly indicators which are available for the same quarter, so that nowcasting is also possible. For the quarters in which no observations are available for the monthly indicators either, the Kalman smoother acts exactly as the Kalman filter. In this way, we obtain iterative multistep forecasts and an estimate of the expected value of GDP growth in each month.

3.3. The MIDAS approach

MIDAS regressions are essentially tightly parameterized, reduced form regressions that involve processes sampled at different frequencies. The response to the higher-frequency explanatory variable is modelled using highly parsimonious distributed lag polynomials, in order to prevent the proliferation of parameters that might result otherwise, as well as to avoid the issues related to lag-order selection (see Andreou, Ghysels, & Kourtellos, 2010, Ghysels, Santa-Clara, & Valkanov, 2006).

3.3.1. The basic MIDAS model

MIDAS models are a direct forecasting tool, relying directly on current and lagged indicators for estimating the current and future GDP. This yields different models for different forecasting horizons. The forecast model for horizon $h_q = h_m/3$ is:

$$y_{t_q+h_q} = y_{t_m+h_m} = \beta_0 + \beta_1 b(L_m, \theta)\, x^{(3)}_{t_m+w} + \varepsilon_{t_m+h_m}, \tag{9}$$

where y_{t_m} and x_{t_m} are the GDP growth and the monthly indicator respectively, $x^{(3)}_{t_m}$ is the corresponding skip-sampled monthly indicator, $w = T^x_m - T^y_m$, and $b(L_m, \theta)$ is the exponential Almon lag,

$$b(L_m, \theta) = \sum_{k=0}^{K} c(k, \theta) L^k_m, \qquad c(k, \theta) = \frac{\exp\left(\theta_1 k + \theta_2 k^2\right)}{\sum_{k=0}^{K} \exp\left(\theta_1 k + \theta_2 k^2\right)}. \tag{10}$$

We estimate the MIDAS model using nonlinear least squares (NLS) in a regression of y_{t_m} on $x^{(3)}_{t_m-k}$, yielding coefficients $\widehat{\theta}_1, \widehat{\theta}_2, \widehat{\beta}_0$ and $\widehat{\beta}_1$. Since the model is h-dependent, we reestimate it for multi-step forecasts and when new information becomes available. The forecast is given by:

$$\widehat{y}_{T^y_m+h_m|T^x} = \widehat{\beta}_0 + \widehat{\beta}_1 B\left(L^{1/m}; \widehat{\theta}\right) x^{(3)}_{T^x_m}. \tag{11}$$

As far as the specification is concerned, we use a large variety of initial parameter specifications, compute the residual sum of squares from Eq. (9), and choose the parameter set which gives the smallest RSS as initial values for the NLS estimation. In the exponential Almon lag function, K is fixed at 12, and the parameters are restricted to $\theta_1 < 5$ and $\theta_2 < 0$.

3.3.2. An extension: the AR-MIDAS model

A natural extension of the basic MIDAS model is the introduction of an autoregressive term. Including the AR dynamics is desirable but not straightforward. Ghysels, Santa-Clara, and Valkanov (2005) show that the introduction of lagged dependent variables creates efficiency losses. Moreover, it would result in the creation of seasonal patterns in the explanatory variables.

We therefore follow Clements and Galvao (2008) and introduce the AR dynamics as a common factor, to rule out seasonal patterns. We estimate the AR-MIDAS, defined as:

$$y_{t_m+h_m} = \beta_0 + \lambda y_{t_m} + \beta_1 b\left(L_m, \theta\right) \times \left(1 - \lambda L_m^3\right) x_{t_m+w}^{(3)} + \varepsilon_{t_m+h_m}, \tag{12}$$

where the λ coefficient can be estimated by NLS together with the other coefficients. Even in this case, we follow the procedure described for the MIDAS approach: first compute the RSS from Eq. (12), then choose the parameters that minimize it and use them as initial values for the NLS estimation.

4. Results for Euro area GDP components

Several papers in the literature to date have tried to nowcast Euro area GDP growth by exploiting mixed-frequency information. Kuzin, Marcellino, and Schumacher (2011) compare various specifications of MIDAS and MF-VAR models with single indicators, as well as combinations of these models. In a second paper, Kuzin, Marcellino, and Schumacher (2013) investigate the performances of a large number of MIDAS and factor models with different specifications for several countries. In this paper, we extend the analysis of Kuzin et al. (2011, 2013) in different ways. Specifically, we focus on nowcasting the quarterly growth rates of Euro area GDP components (from the production and expenditure side), using a very large set of monthly indicators (around 150 monthly series) and a wide range of forecasting methods. Furthermore, we consider a different sample to that used by Kuzin et al. (2011, 2013), one which includes the financial crisis, as well as a different set of indicators. Moreover, bridge models are assessed in our analysis, since they are one of the simplest and most popular methods of exploiting the mixed-frequency information employed by central banks.

The analysis conducted by Kuzin et al. (2011) shows that the MIDAS model without an AR component generally performs worse than the MIDAS specification that includes it. Therefore, in what follows we focus only on models with an autoregressive term, namely, bridge equations (with autoregressive lags), AR-MIDAS, and MF-VAR models.

In this section, we discuss the results of individual models for three nowcast horizons. We consider the MSE as a measure for comparing the performances of the different models. As a benchmark, we use a recursively estimated AR model for each component under consideration, the lag length of which is specified according to the BIC. We also considered the recursively estimated in-sample mean as a benchmark, but since the resulting MSE is usually greater than the MSE of the AR model, we prefer to adopt the latter.

Table 2 provides evidence on the average performances of the different classes of mixed-frequency models, in order to investigate their properties and capture their differences and similarities over the full set of individual indicators. The table reports the average relative MSE performances for each GDP component, at different horizons, against the AR benchmark. First, we estimate every individual model and compute the relative MSE with respect to the benchmark, i.e., we calculate the MSE of every single indicator model relative to the MSE of the AR model. Then, we average across all of the indicators within a model class (Bridge, MIDAS, AR-MIDAS and MF-VAR).

The evidence is quite in favour of the exploitation of monthly information when nowcasting the different GDP components, with mild differences depending on which component we are focusing on. In more detail, looking at the GDP disaggregation from the production side, the mixed-frequency approaches outperform the benchmark for those components for which several monthly indicators are available, as in the case of the industry sector and financial services. For agriculture, the lack of availability of monthly indicators is critical. The same is true for the last branch, which includes a variety of economic activities (public administration and defence, compulsory social security; education; health and social work; other community, social and personal service activities; private households with employed persons), for which it is not easy to find reliable and timely monthly indicators of the value they add.

As a general remark, the AR-MIDAS seems to work particularly well for short horizons. The evidence in favour of MF-VAR is less strong, while the bridge models perform well, beating the benchmark in many cases.

Looking now at the expenditure components, we reach similar conclusions. Since it is very hard to find monthly indicators for the government final consumption, it is very difficult to beat the benchmark (no gains from using monthly indicators appear at any horizons). For most of the other components, bridge equations and AR-MIDAS perform better than the benchmark. The MF-VAR approach has a less clear cut performance in this case too, but it performs better than the benchmark when $h_m = 2, 3$ for some components.

As another way to compare the alternative mixed frequency models, we compute the MSEs of the AR-MIDAS and MF-VAR models relative to the MSE of the bridge equations for each single indicator, then average over all of the relative MSEs we obtain. The results are shown in Table 3.

The only method with some ability to beat the bridge equations is AR-MIDAS. For the GDP components from the

Table 2
Average relative MSE performances of different classes of mixed-frequency models against AR benchmark: GDP components.

		Horizon (h_m)					Horizon (h_m)		
Component	Model	1	2	3	Component	Model	1	2	3
Production side					**Expenditure side**				
Agriculture, hunting, forestry and fishing	bridge	**0.76**	**0.98**	**0.98**	Final consumption - households	bridge	**1.01**	0.96	0.93
	ar-midas	0.80	1.10	1.10		ar-midas	1.02	**0.85**	**0.85**
	mf-var	**0.76**	1.04	1.01		mf-var	1.10	0.98	0.95
Total industry, excluding construction	bridge	1.06	0.90	**0.93**	Final consumption - Government	bridge	**1.07**	**1.06**	**1.05**
	ar-midas	**0.92**	**0.89**	0.95		ar-midas	1.10	1.12	1.08
	mf-var	1.45	0.94	0.98		mf-var	1.41	1.63	1.56
Construction	bridge	1.01	**1.07**	**1.05**	Gross fixed capital formation	bridge	1.08	1.04	1.05
	ar-midas	**0.98**	1.10	1.09		ar-midas	**0.93**	**0.92**	**0.95**
	mf-var	1.02	1.95	1.07		mf-var	1.38	1.14	1.18
Trade, hotels and restaurants, transport and communication services	bridge	1.10	1.10	1.11	Imports	bridge	0.85	0.87	0.90
	ar-midas	**1.05**	**0.92**	**0.94**		ar-midas	**0.82**	**0.79**	**0.83**
	mf-var	1.22	1.12	1.15		mf-var	1.03	0.91	0.96
Financial services and business activities	bridge	0.84	0.83	0.87	Exports	bridge	0.94	0.88	0.92
	ar-midas	**0.83**	**0.77**	**0.81**		ar-midas	**0.91**	**0.86**	**0.91**
	mf-var	0.86	0.85	0.91		mf-var	1.16	0.92	0.98
Other services	bridge	**1.00**	**1.01**	**1.01**					
	ar-midas	1.09	1.20	1.15					
	mf-var	1.15	1.14	1.11					

Notes: The entries in the table are obtained as follows: first, estimate every individual model recursively and compute the relative MSE with respect to the benchmark; then, take the average of the relative MSE within a model class across all of the indicators. The benchmark is the recursive estimate of an AR model with the lag length specified accordingly to the BIC. The evaluation sample is 2003Q1–2009Q1. The numbers in bold show the best relative MSE performance for each horizon and each component.

Table 3
Average relative MSE performances of different classes of mixed-frequency models against bridge models: GDP components.

		Horizon (h_m)					Horizon (h_m)		
Component	Model	1	2	3	Component	Model	1	2	3
Production side					**Expenditure side**				
Agriculture, hunting, forestry and fishing	ar-midas	1.05	1.11	1.12	Final consumption - households	ar-midas	1.03	**0.89**	**0.92**
	mf-var	**0.99**	1.06	1.04		mf-var	1.09	1.03	1.04
Total industry, excluding construction	ar-midas	**0.88**	1.00	1.03	Final consumption - Government	ar-midas	1.04	1.06	1.04
	mf-var	1.36	1.05	1.06		mf-var	1.32	1.51	1.45
Construction	ar-midas	**0.98**	1.03	1.05	Gross fixed capital formation	ar-midas	**0.89**	**0.91**	**0.92**
	mf-var	1.02	1.92	1.03		mf-var	1.31	1.13	1.16
Trade, hotels and restaurants, transport and communication services	ar-midas	**0.97**	**0.86**	**0.87**	Imports	ar-midas	**0.96**	**0.94**	**0.94**
	mf-var	1.12	1.05	1.06		mf-var	1.19	1.06	1.08
Financial services and business activities	ar-midas	1.03	**0.97**	**0.98**	Exports	ar-midas	**0.97**	1.01	1.01
	mf-var	1.07	1.09	1.09		mf-var	1.22	1.05	1.07
Other services	ar-midas	1.09	1.18	1.13					
	mf-var	1.16	1.13	1.10					

Notes: The entries in the table are obtained as follows: first, estimate every individual model recursively, and compute the relative MSE with respect to the corresponding bridge model; then, take the average of the relative MSE within a model class across all of the indicators. The evaluation sample is 2003Q1–2009Q1. The numbers in bold show where the model considered performed better than the bridge model.

expenditure side, the AR-MIDAS model often outperforms the other approaches. For the production side, the evidence is more mixed. Depending on the component, bridge models either outperform AR-MIDAS or perform equally well.

5. Forecast pooling

The availability of many indicators leads to many forecasts of the same variable. This suggests the idea of exploiting the information in the individual forecasts and combining them. Implementing forecast combination allows us to partially overcome misspecification biases, parameter instability and measurement errors in the datasets which may be present in the individual forecasts (see Timmermann, 2006, for a detailed overview of forecast combination).

Estimating combination weights is hard, since a large data sample relative to the number of the models is required in order to obtain appropriate estimates of the weights. Hence, here we provide results from forecast combinations within the same class of models, based on

Table 4
Relative MSE performance of model pooling within a given class of models against the AR benchmark (combination scheme: median).

Component	model	Horizon (h_m) 1	2	3	Component	Model	Horizon (h_m) 1	2	3
Production side					**Expenditure side**				
Agriculture, hunting, forestry and fishing	bridge	0.74*	**0.95**	**0.95**	Final consumption - households	bridge	0.97*	0.96*	0.97*
	ar-midas	0.75*	1.02	1.02		ar-midas	**0.92***	**0.71***	**0.79***
	mf-var	**0.69***	0.96	**0.95**		mf-var	0.95*	0.93*	0.96*
	all	0.73*	0.96	**0.95**		all	0.94*	0.85*	0.88*
Total industry, excluding construction	bridge	1.00*	0.96	0.96	Final consumption - Government	bridge	**1.00**	**1.00**	1.00*
	ar-midas	**0.90***	**0.89**	**0.95**		ar-midas	1.01	1.01	1.02
	mf-var	1.19	0.97*	1.01		mf-var	1.11	1.04*	1.03
	all	1.00	0.94*	0.96		all	1.01	**1.00**	**0.99**
Construction	bridge	0.92	**0.98**	**0.99**	Gross fixed capital formation	bridge	1.08	1.12	1.12
	ar-midas	0.93	1.03	1.04		ar-midas	**0.88***	**0.91**	**0.94**
	mf-var	**0.88**	0.99	1.00		mf-var	1.27	1.12	1.20
	all	0.92*	1.00	1.01		all	1.00	0.98	1.03
Trade, hotels and restaurants, transport and communication services	bridge	1.18*	1.22	1.23	Imports	bridge	0.87	0.93	0.94
	ar-midas	**1.01**	**0.91***	**0.94***		ar-midas	**0.81***	**0.76**	**0.79**
	mf-var	1.17	1.14	1.17		mf-var	0.96	0.89*	1.00
	all	1.09	1.02	1.05		all	0.86*	0.85*	0.89
Financial services and business activities	bridge	0.72*	0.74*	0.85	Exports	bridge	0.97	0.95	0.97
	ar-midas	0.73*	**0.66***	**0.77**		ar-midas	**0.90***	**0.83***	**0.90**
	mf-var	**0.71***	0.79*	0.92		mf-var	1.07	0.93*	1.01
	all	0.72*	0.74*	0.84		all	0.95*	0.90*	0.95
Other services	bridge	0.96*	**0.98**	**1.00**					
	ar-midas	**0.95**	0.99	1.03					
	mf-var	0.99	1.02	1.03*					
	all	**0.95**	0.99	1.01					

Notes: The entries in the table are obtained as follows: first, forecasts from single indicator models are computed, and the median of all of the forecasts within a single model is obtained; second, the MSE of the forecast combination is calculated and divided by the MSE of the benchmark. Only the last row of each component considers the median of all of the forecasts across methods. The estimation is conducted recursively. The benchmark is the recursive estimate of an AR model with the lag length specified according to the BIC. The evaluation sample is 2003Q1–2009Q1. The numbers in bold show the best relative MSE performance for each horizon and each indicator. Asterisks indicate the models which appear to be statistically superior to the benchmark at a confidence level of 10% according to the modified Diebold–Mariano test.

a simple combination scheme, the median—the simplest rank-based weighting scheme.[7]

In Table 4, we provide the relative MSE performance of model pooling within a given class of models against the benchmark, for each component of the GDP. The steps we conduct are as follows: first, forecasts from single indicator models are computed, and the median of all of the forecasts within a single approach is obtained. Second, the MSE of this forecast combination is calculated and divided by the MSE of the benchmark. Since we are comparing one forecast with the benchmark in this case, we can test the hypothesis of equal accuracy in forecasting performance, using the Diebold–Mariano test which has been modified for short samples (see Harvey, Leybourne, & Newbold, 1997).

The results show that AR-MIDAS pooling performs fairly well: it outperforms the benchmark for most of the components at each nowcast horizon. Bridge models confirm their good performances across horizons. Pooling improves the performance for single indicators for the MF-VARs as well, although the gains with respect to the benchmark are smaller than for the other approaches. Table 4 also contains the results of nowcast combinations of all of the models under consideration. We notice that, in general, pooling all of the models is not better than pooling within single classes of models.

In terms of statistical accuracy, the forecasts obtained using the mixed-frequency approach turn out to be statistically different from those of the AR benchmark (at a 10% significance level) in a few cases, especially for the best performing models (the cases in which the hypothesis of equal accuracy is rejected are indicated by a star in Table 4). Despite the very short evaluation sample here, which generally compromises a good performance of the test, we obtain evidence of the improvement in the forecast accuracy by using mixed-frequency data.

[7] The results from two other simple combination schemes (the mean, which is the most exploited method in the literature, and a weighted mean that lets the combination weights be inversely proportional to the MSE of the previous four-quarter performance of the model; see Stock & Watson, 2001) are available upon request. Aiolfi and Timmermann (2006) also propose more sophisticated combination schemes which produce improved forecasts, based on information on past forecasting performances. However, since the number of forecasts to be combined in our case is far larger than the number of observations in our sample, we decided to consider only the easiest combination schemes, one of which is also based on the same principle of weighting the different forecasts based on the past performances of the models.

It is also worth mentioning that the largest improvements upon the AR benchmark are for the components for which many indicators are available in the dataset. For the other variables, there are still improvements (unlike in the single indicator case), but these are generally smaller.

In summary, and in line with the forecast combination literature (e.g., Timmermann, 2006), pooling mixed frequency models based on a large set of alternative indicators appears promising.

6. Large scale models

In our empirical analysis, we use a very large dataset with many series, with the aim of capturing the movements in the euro area economy. The information included in these time series can be summarized in a few factors that represent the key economic driving forces. Therefore, factor models, which have a long tradition in econometrics, are also appealing from an economic point of view.

So far, we have tried to combine the information from the different indicators by combining forecasts based on different individual equations which contain one indicator each. Now, with the use of factor models, instead of pooling forecasts, we pool the information contained in the dataset and summarize it into a few factors.

In what follows, we compare the results obtained from a standard quarterly factor model (see Stock & Watson, 2002) with those obtained from the approach recently proposed in the literature by Marcellino and Schumacher (2010), the Factor-MIDAS, which merges factor models based on large datasets with the forecast methods based on MIDAS.

6.1. Quarterly factor model

We employ the standard factor model proposed by Stock and Watson (2002). The h_q-step-ahead forecast model is:

$$y_{t+h_q} = \beta_0 + \beta\left(L_q\right)\widehat{f}_{t_q} + \lambda\left(L_q\right)y_{t_q} + \varepsilon_{t_q+h_q}, \tag{13}$$

where $\beta\left(L_q\right)$ is an unrestricted lag polynomial of lag order P and $\lambda\left(L_q\right)$ is of order R. The estimation is conducted using a two-step procedure. First, the quarterly dataset, obtained by aggregating the monthly indicators over time, is used to estimate the factors by principal component analysis (PCA). Second, the estimators $\widehat{\beta}_0, \widehat{\beta}\left(L_q\right)$ and $\widehat{\lambda}\left(L_q\right)$ are obtained by regressing y_{t+h_q} onto a constant, $\widehat{f}_{t_q}$ and y_{t_q} and lags. The forecast is then formed as $\widehat{y}_{t+h_q} = \widehat{\beta}_0 + \widehat{\beta}\left(L_q\right)\widehat{f}_{t_q} + \widehat{\lambda}\left(L_q\right)y_{t_q}$. In our application, we choose a quarterly model with a fixed number of factors (one) and the number of lags chosen by the BIC.

6.2. Factor-MIDAS models

It is possible to augment the MIDAS regressions with the factors extracted from a large dataset in order to obtain a richer family of models that exploits large high-frequency datasets for predicting low-frequency variables. While the basic MIDAS framework consists of a regression of a low-frequency variable on a set of high-frequency indicators, the Factor-MIDAS approach exploits estimated factors rather than single or small groups of economic indicators as regressors.

The Factor-MIDAS model for a forecast horizon of h_q quarters with $h_q = h_m/3$ is

$$y_{t_q+h_q} = y_{t_m+h_m} = \beta_0 + \beta_1 b\left(L_m;\theta\right)\widehat{f}^{(3)}_{t_m+w} + \varepsilon_{t_m+h_m}, \tag{14}$$

where $b\left(L_m;\theta\right) = \sum_{k=0}^{K} c\left(k;\theta\right)L_m^k$ and $c\left(k;\theta\right) = \frac{\exp\left(\theta_1 k+\theta_2 k^2\right)}{\sum_{k=0}^{K}\exp\left(\theta_1 k+\theta_2 k^2\right)}$. As was described in the MIDAS models above, the exponential lag function provides a parsimonious way to consider monthly lags of the factors.

The model can be estimated using nonlinear least squares in a regression of y_{t_m} on the factors $\widehat{f}^{(3)}_{t_m+w-h}$. The forecast is given by

$$y_{T_m+h_m|T_m+w} = \widehat{\beta}_0 + \widehat{\beta}_1 b\left(L_m;\widehat{\theta}\right)\widehat{f}^{(3)}_{T_m+w}. \tag{15}$$

The projection is then based on the final values of the estimated factors.

MIDAS regression can be extended with the addition of autoregressive dynamics as follows:

$$\begin{aligned} y_{t_q+h_q} &= y_{t_m+h_m} = \beta_0 + \lambda y_{t_m} \\ &\quad + \beta_1 b\left(L_m;\theta\right)\widehat{f}^{(3)}_{t_m+w} + \varepsilon_{t_m+h_m}. \end{aligned} \tag{16}$$

The two-step procedure described for quarterly factor models can also be used in the case of mixed-frequency data. In order to handle the ragged-edge structure of the dataset, we follow the procedure outlined by Stock and Watson (2002), which combines the EM algorithm with PCA. Since not all observations are available, due to publication lags, the authors write the relationship between observed and not fully observed variables as

$$X_i^{\text{obs}} = A_i X_i, \tag{17}$$

where X_i^{obs} contains the observations available for variable i as a subset of X_i, and A_i is the matrix that tackles missing values. Taking this relationship into account, the EM algorithm provides estimates of the missing values (for more details, see Marcellino & Schumacher, 2010, and Stock & Watson, 2002).

In the next section we only provide the results for the case of models with one factor. The EM algorithm is used to interpolate the missing values, but the pairwise covariances are computed over the periods when both series are available, to avoid convergence problems. Marcellino and Schumacher (2010) compare this case with a similar application for forecasting German GDP growth using a larger number of factors, and find only minor differences in the results.

6.3. Results

Nowcast results for the Factor-MIDAS and the more standard quarterly factor model are presented in Table 5. The numbers in the table show the MSE of each model relative to that of the benchmark, which once again is an AR process with a lag length selected according to the BIC.

Table 5
Relative MSE performances of different classes of factor models against the AR benchmark: GDP components.

Component	Model	Horizon (h_m) 1	2	3	Component	Model	Horizon (h_m) 1	2	3
Production side					**Expenditure side**				
Agriculture, hunting, forestry and fishing	Factor-MIDAS	0.81	1.07	1.15	Final consumption - households	Factor-MIDAS	0.69*	0.59*	0.59
	Quarterly factor model	0.69*	0.98	0.98		Quarterly factor model	1.07	0.69	0.69
Total industry, excluding construction	Factor-MIDAS	0.58*	0.67	0.72	Final consumption - Government	Factor-MIDAS	0.97	1.10	1.03
	Quarterly factor model	0.90	0.98	0.98		Quarterly factor model	0.96	0.94*	0.94*
Construction	Factor-MIDAS	0.83	1.01	0.93	Gross fixed captial formation	Factor-MIDAS	0.63*	0.66	0.67
	Quarterly factor model	0.98	1.10	1.10		Quarterly factor model	1.11	1.09*	1.09*
Trade, hotels and restaurants, transport and communication services	Factor-MIDAS	0.56*	0.55	0.59	Imports	Factor-MIDAS	0.67	0.51	0.60
	Quarterly factor model	0.93	0.89	0.89		Quarterly factor model	0.50*	0.99	0.99
Financial services and business activities	Factor-MIDAS	0.40*	0.45*	0.46	Exports	Factor-MIDAS	0.62*	0.63	0.68
	Quarterly factor model	0.64*	0.92	0.92		Quarterly factor model	0.75	0.91	0.91
Other services	Factor-MIDAS	1.00	0.96	1.04					
	Quarterly factor model	0.87	1.00	1.00					

Notes: The entries in the table are obtained as follows: first, estimate every factor model recursively, then compute the relative MSE with respect to the benchmark. The factors are estimated using the EM algorithm together with PCA, as per Stock and Watson (2002). The benchmark is the recursive estimate of an AR model with the lag length specified accordingly to the BIC. The evaluation sample is 2003Q1–2009Q1. The numbers in bold show the best relative MSE performance for each horizon and each indicator. Asterisks indicate the models which appear to be statistically superior to the benchmark at a confidence level of 10% according to the modified Diebold–Mariano test.

As a general result, there is evidence that the nowcasting performance benefits a lot from the use of a large information set, summarized by factors. Factor models behave particularly well, relative to both the individual models in Section 4 and the pooled forecast in Section 5. The standard quarterly factor model also performs better than the benchmark. The evidence is in favour of the use of factor-MIDAS models for predicting the quarterly growth of each component for which the dataset contains enough useful information. The evidence is also confirmed by the results of the modified Diebold–Mariano test, in many cases.

Finally, comparing the results in Table 5 with those on forecast pooling in Table 4, it turns out that pooling information into a factor model generally provides better results than pooling the forecasts from different individual models.

7. Evidence for Euro area GDP growth

One major novelty in our analysis thus far is that, instead of focusing on the Euro area GDP growth, we have looked at the different components from the production and expenditure side. In order to complete our analysis, we now focus on the analysis of aggregate GDP growth. The aim here is to combine the forecasts of the different components, and to see whether this leads to improvements relative to the approach of forecasting GDP growth directly.

The aggregation of the different component forecasts is a rather complex issue (in this respect, see the analysis by Frale, Marcellino, Mazzi, & Proietti, 2011). However, to keep it simple, we aggregate the components based on constant weights computed based on an OLS regression of the total GDP on the components.[8] Therefore, what we do is to aggregate the forecasts obtained for the different components using the different approaches, and compare them with the forecasts obtained using the same methods but for the aggregate measure.

Table 6 summarizes the forecasting results from single indicator models, forecast pooling and factor models (all computed as described in the previous sections for the components), obtained by aggregating the components from the production and expenditure sides. In the last column, it then reports the nowcast results obtained from the aggregated GDP directly. The values in the table are ratios relative to the AR benchmark on the aggregate GDP. The use of mixed-frequency information is important in improving the forecasting performances of the models, especially when focusing on the aggregate measure. In general, it seems that the chief gains are obtained with a direct approach, although there are a few exceptions,

[8] We compute the weights on the estimation sample, to avoid using information included in the evaluation sample. Moreover, the use of weights obtained from an OLS regression allows us to take discrepancies in the measures into account, and to avoid considering the taxes and subsidies on products (which are not allocated to sectors and industries in the decomposition from the production side).

Table 6
Nowcasting results for GDP growth: direct vs. aggregation approaches.

	Model	Aggregation from the production side Horizon (h_m) 1	2	3	Aggregation from the expenditure side Horizon (h_m) 1	2	3	Direct approach Horizon (h_m) 1	2	3
Single indicator models vs. AR benchmark	bridge	1.27	**0.82**	**0.84**	1.41	**0.76**	**0.78**	0.99	0.88	0.91
	ar-midas	1.12	0.86	0.92	1.10	0.86	0.92	0.88	0.82	0.87
	mf-var	1.50	**0.98**	**1.03**	1.53	1.00	1.04	1.37	0.99	1.04
	ar (combined)	1.24	1.00	1.00	1.24*	1.04	1.04	–	–	–
Pooling within a class of indicators vs. benchmark	bridge	1.24	1.01	1.04	1.27*	1.03	1.04	0.99*	0.94	0.96
	ar-midas	1.10*	0.86	0.92	1.11*	0.84	0.93	0.86*	0.80	0.88
	mf-var	1.33*	**1.01**	**1.07**	1.44*	**1.02***	**1.07**	1.23*	1.03*	1.09
Factor models vs. benchmark	Factor-MIDAS	**0.60***	**0.55**	0.60	0.68*	0.62	0.64	0.68*	0.57	0.59
	Quarterly FM	**0.93**	0.98	0.98	0.98	0.83	0.83	0.95	0.83	0.83

Notes: The table reports the nowcasting results for GDP growth obtained using different approaches. The results in the first two panels refer to nowcasts obtained by aggregating the results from the different components of GDP, disaggregated from the production and expenditure side. The last panel reports the results obtained by computing the nowcasts on the aggregate measure directly. The benchmark is an AR process estimated on the aggregate measure of GDP, with the lag length selected according to the BIC. For a description of the way in which the entries in the table are obtained, refer to the corresponding tables for the GDP components. The evaluation sample is 2003Q1–2009Q1. The numbers in bold represent the cases in which the aggregated approach is superior to the direct approach. Asterisks indicate the models which appear to be statistically superior to the benchmark at a confidence level of 10% according to the modified Diebold–Mariano test.

specifically the bridge equations and the factor-MIDAS, in which cases aggregating the forecasts following the decomposition of the GDP from the expenditure side improves the forecasting performance.

This shows that, despite our simple method based on weights computed by OLS, there is still room of improvement in forecasting GDP growth by exploiting the disaggregated information in the GDP components.

8. Conclusions

This paper extends the analysis which has appeared in the literature to date, considering a dataset of more than 150 monthly indicators for nowcasting quarterly Euro area GDP components from the production and expenditure sides, and comparing different econometric approaches that take into account the mixed frequency and ragged edge structure of the dataset.

To start with, we compared the bridge model, the MIDAS model with its extension incorporating an AR component, and the MF-VAR. The three approaches display some marked differences: while the bridge equations are a rather simple approach, which still relies partially on aggregation, the other models presented in this paper are more sophisticated and deal with an unbalanced dataset in various different ways. Just as one example, while MIDAS is a single-equation approach and a direct multi-step forecasting tool, MF-VAR explains the indicator and GDP growth jointly, and is an iterative instrument for producing multi-step forecasts. Moreover, while we obtain a monthly update of the quarterly GDP growth with bridge equations and MIDAS models, using the state space approach means that we can also have an estimate of the monthly missing values of the GDP.

These approaches are therefore too different to be ranked based only on theory. Hence, it is preferable to compare them in empirical applications. The main results we obtained from our exercise hint at a better performance of MIDAS models, especially for the short horizons. Bridge models, which are less sophisticated than the other approaches, also perform well overall, being the best approach to use for some components. Finally, MF-VAR is the least promising mixed-frequency approach overall, at least for very short horizons.

Pooling within each class of models turns out to be a good strategy for improving the performance: the MSEs of the forecast combinations are smaller than the MSEs of most of the individual models at every horizon. Comparing the different performances of forecast combinations within each class, AR-MIDAS and bridge models appear to be the best strategies.

Even better performances are obtained using factor models, confirming that pooling information from a large number of series is useful in short-term forecasting and reduces the MSE. In particular, we looked at the factors estimated using the EM algorithm and PCA, and included these factors in a MIDAS framework. The factor-MIDAS with the inclusion of the AR component is the best for most components, in terms of relative MSEs.

Finally, we tested the robustness of our findings about Euro area GDP components by aggregating their forecasts to obtain a comparison with the direct nowcast of the total Euro area GDP growth. The findings for the aggregated nowcasts are promising, meaning that there is scope for forecasting the single components to shed light on the total GDP measure.

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Appendix. Dataset description

MONTHLY DATA	log/diff
HICP - All items excluding energy and unprocessed food	5
HICP - All items excluding energy, food, alcohol and tobacco	5
HICP - All items excluding energy and seasonal food	5
HICP - All items excluding energy	5
HICP - All items excluding tobacco	5
HICP - All items (HICP=Harmonized Index of Consumer Prices)	5
HICP - Food and non alcoholic beverages	5
HICP - Alcoholic beverages and tobacco	5
HICP - Clothing and footwear	5
HICP - Housing, water, electricity,gas and other fuels	5
HICP - Furnishings, household equipment and maintenance	5
HICP - Health	5
HICP - Transport	5
HICP - Communication	5
HICP - Recreation and culture	5
HICP - Education	5
HICP - Hotels, cafes and restaurants	5
HICP - Miscellaneous goods and services	5
HICP - Energy	5
HICP - Food	5
Producer price index - Electricity, gas, steam and air conditioning supply	5
Producer price index - Industry (except construction), sewerage, waste management and remediation activities	5
Producer price index - Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply	5
Producer price index - Mining and quarrying	5
Producer price index - B_TO_E36	5
Producer price index - Manufacturing	5
Producer price index - Manufacturing, for new orders	5
Producer price index - Electricity, gas, steam and air conditioning supply	5
Producer price index - Water collection, treatment and supply	5
Producer price index - Capital goods	5
Producer price index - Consumer goods	5
Producer price index - Durable consumer goods	5
Producer price index - Intermediate goods	5
Producer price index - Non-durable consumer goods	5
Producer price index - Energy	5
Business surveys - Construction - Construction confidence indicator	1
Business surveys - Construction - Employment expectations for the months ahead	1
Business surveys - Construction - Assessment of order books	1
Business surveys - Construction - Price expectations for the months ahead	1
Business surveys - Construction - Trend of activity compared with preceding months	1
Business Climate Indicator	1
Consumer confidence indicator	1
Consumer surveys - Financial situation over the last 12 months	1
Consumer surveys - Financial situation over the next 12 months	1
Consumer surveys - General economic situation over the last 12 months	1
Consumer surveys - General economic situation over the next 12 months	1
Consumer surveys - Major purchases over the next 12 months	1
Consumer surveys - Major purchases at present	1
Consumer surveys - Price trends over the last 12 months	1
Consumer surveys - Price trends over the next 12 months	1
Consumer surveys - Statement on financial situation of household	1
Consumer surveys - Savings over the next 12 months	1
Consumer surveys - Savings at present	1
Consumer surveys - Unemployment expectations over the next 12 months	1
Business surveys - Industry - Industrial confidence indicator	1
Business surveys - Industry - Employment expectations for the months ahead	1
Business surveys - Industry - Assessment of export order-book levels	1
Business surveys - Industry - Assessment of order-book levels	1
Business surveys - Industry - Expectations for the months ahead	1
Business surveys - Industry - Production trend observed in recent months	1
Business surveys - Industry - Assessment of stocks of finished products	1

Business surveys - Industry - Selling price expectations for the months ahead	1
Business surveys - Retail - Assessment of stocks	1
Business surveys - Retail - Retail confidence indicator	1
Business surveys - Retail - Expected business situation	1
Business surveys - Retail - Employment	1
Business surveys - Retail - Orders placed with suppliers	1
Business surveys - Retail - Present business situation	1
Business survey - Services - Assessment of business climate	1
Business survey - Services - Evolution of demand expected in the months ahead	1
Business survey - Services - Evolution of demand in recent months	1
Business survey - Services - Services Confidence Indicator	1
Business survey - Services - Evolution of employment in recent months	1
Construction confidence indicator	1
Consumer confidence indicator	1
Economic sentiment indicator	1
Industrial confidence indicator	1
Retail confidence indicator	1
Services Confidence Indicator	1
Unemployment rate according to ILO definition - Over 25 years	2
Unemployment rate according to ILO definition - Under 25 years	2
Unemployment rate according to ILO definition	2
Unemployment according to ILO definition - Over 25 years - Total	1
Unemployment according to ILO definition - Under 25 years - Total	1
Unemployment according to ILO definition - Total	1
Production index	5
Production index - Buildings	5
Production index - Civil engineering works	5
Production index - Construction	5
Production index - Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply	5
Production index - Mining and quarrying; manufacturing	5
Production index - Mining and quarrying	5
Production index - Manufacturing	5
Production index - Manufacturing, for new orders	5
Production index - Electricity, gas, steam and air conditioning supply	5
Production index - Capital goods	5
Production index - Consumer goods	5
Production index - Durable consumer goods	5
Production index - Intermediate goods	5
Production index - Non-durable consumer goods	5
Turnover index - domestic market - Mining and quarrying; manufacturing	5
Turnover index - non-domestic market - Mining and quarrying; manufacturing	5
Turnover index - total - Mining and quarrying; manufacturing	5
Turnover index - domestic market - Manufacturing	5
Turnover index - non-domestic market - Manufacturing	5
Turnover index - total - Manufacturing	5
Turnover index - domestic market - Manufacturing, for new orders	5
Turnover index - non-domestic market - Manufacturing, for new orders	5
Turnover index - total - Manufacturing, for new orders	5
Turnover index - domestic market - Capital goods	5
Turnover index - non-domestic market - Capital goods	5
Turnover index - non-domestic market - Capital goods	5
Turnover index - total - Capital goods	5
Turnover index - domestic market - Consumer goods	5
Turnover index - non-domestic market - Consumer goods	5
Turnover index - total - Consumer goods	5
Turnover index - domestic market - Durable consumer goods	5
Turnover index - non-domestic market - Durable consumer goods	5
Turnover index - total - Durable consumer goods	5
Turnover index - domestic market - Intermediate goods	5
Turnover index - non-domestic market - Intermediate goods	5
Turnover index - total - Intermediate goods	5
Turnover index - domestic market - Non-durable consumer goods	5
Turnover index - total - Non-durable consumer goods	5
Hours worked index - Construction	5
New orders received index - Manufacturing, for new orders	5
New orders received index - Manufacturing, for new orders (except heavy transport equipment)	5
Number of new car registrations	5

Deflated turnover index - Retail sale of food, beverages and tobacco	5
Deflated turnover index - Retail trade, except of motor vehicles and motorcycles	5
Deflated turnover index - Retail sale of non-food products (including fuel)	5
Deflated turnover index - Retail sale of non-food products (except fuel)	5
Deflated turnover index - Retail trade, except of motor vehicles, motorcyles and fuel	5
MF-M1-SA Money supply M1 - SA	5
MF-M2-SA Money supply M2 - SA	5
MF-M3-SA Money supply M3 - SA	5
MF-3MI-RT 3-month interest rates (average)	2
MF-LTGBY-RT Long term government bond yields - Maastricht definition (average)	2
Exchange rates US Dollar against the ECU/euro (average)	2
Exchange rates Yen against the ECU/euro (average)	2
Exchange rates Pound Sterling against the ECU/euro (average)	2
DAX share price index	5
DJ EURO STOXX 50, price index	5
EM government bond yield - 2 year	2
EM government bond yield - 3 year	2
EM government bond yield - 5 year	2
EM government bond yield - 7 year	2
EM government bond yield - 10 year	2
Germany interbank 12 month - offered rate	2
Germany interbank 3 month - offered rate	2
Germany interbank 6 month - offered rate	2
German yields on fully taxed bonds outstanding - all bank bonds	2
German yields on fully taxed bonds outstanding - corporate bonds	2

Notes: log/diff: 1: unchanged; 2: first differencing, no logs; 3: second differencing, no logs; 4: only logs; 5: first differencing, logs; 6: second differencing, logs.

QUARTERLY DATA	log/diff
Gross value added at constant prices (mio euro) - Agriculture, hunting, forestry and fishing	5
Gross value added at constant prices (mio euro) - Total industry (excluding construction)	5
Gross value added at constant prices (mio euro) - Construction	5
Gross value added at constant prices (mio euro) - Wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods; hotels and restaurants; transport, storage and communication	5
Gross value added at constant prices (mio euro) - Financial intermediation; real estate, renting and business activities	5
Gross value added at constant prices (mio euro) - Public administration and defence, compulsory social security; education; health and social work; other community, social and personal service activities; private houselholds with employed persons	5
Gross value added at constant prices (mio euro) - All NACE branches - Total	5
Gross domestic product at market prices - CLV2000	5
Gross value added - CLV2000	5
Final consumption expenditure: household and NPISH - CLV2000	5
Final consumption expenditure: general government - CLV2000	5
Gross fixed capital formation - total - CLV2000	5
Exports - total - CLV2000	5
Imports - total - CLV2000	5

Notes: log/diff: 1: unchanged; 2: first differencing, no logs; 3: second differencing, no logs; 4: only logs; 5: first differencing, logs; 6: second differencing, logs.

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