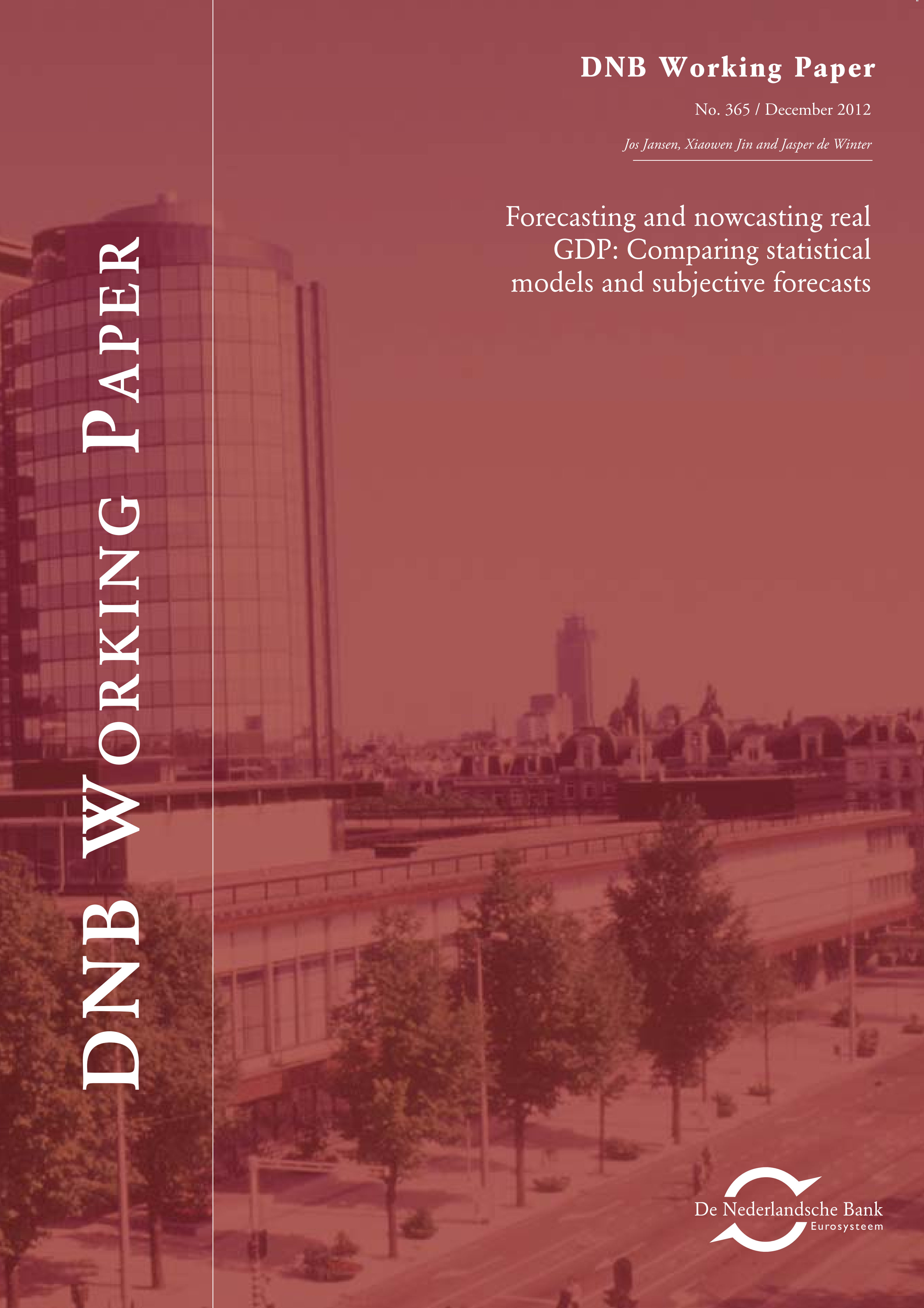

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De Nederlandsche Bank
Eurosysteem

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Forecasting and nowcasting real GDP: Comparing statistical models and subjective forecasts

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Abstract

We conduct a systematic comparison of the short-term forecasting abilities of eleven statistical models and professional analysts in a pseudo-real time setting, using a large set of monthly indicators. Our analysis covers the euro area and its five largest countries over the years 1996-2011. We find that summarizing the available monthly information in a few factors is a more promising forecasting strategy than averaging a large number of indicator-based forecasts. The dynamic and static factor model outperform other models, especially during the crisis period. Judgmental forecasts by professional analysts often embody valuable information that could be used to enhance forecasts derived from purely mechanical procedures.

JEL Classification: E52, C53, C33.
KEYWORDS: nowcasting; professional forecasters; factor model; judgment; forecasting.

1 Introduction

Information on economic activity and its short-term prospects is of great importance to decision makers in governments, central banks, financial markets and non-financial firms. Monetary and economic policy makers and economic agents have to make decisions in real time with incomplete and inaccurate information on current economic conditions. A key indicator of the state of the economy is the growth rate of real GDP, which is available on a quarterly basis only and is also subject to substantial publication lags. In many countries an initial estimate of quarterly real GDP is published around six weeks after the end of the quarter. Moreover, real GDP data are subject to sometimes substantial revisions, as more data becomes available to statistical offices over time.

Fortunately, there is a lot of statistical information related to economic activity that is published on a more frequent and timely basis. This information includes data on industrial production, prices of goods and services, expenditures, unemployment, financial market prices, loans and consumer and business confidence. The forecasting literature has recently developed several statistical approaches to exploit this potentially very large information set in order to improve the

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assessment of real GDP growth in the current quarter (nowcast) and its development in the near future. Examples are bridge models, factor models, mixed-data sampling models (MIDAS) and mixed-frequency vector-autoregressive (MFVAR) models. These models differ in their solutions to the practical problems of how to handle a large-scale information set and the fact that the auxiliary variables are observed at different frequencies and with different publication lags.

For practitioners there is now a wealth of statistical models to choose from. So which one should they use? As each model has its strengths and weaknesses it is difficult to make a choice on purely theoretical grounds. The ranking of the models in terms of forecasting ability and the extent to which this varies with the prediction horizon or the economic circumstances has to be determined by empirical analysis. On these issues the jury is still out, however, as large-scale comparative studies are scarce. The empirical work in many papers refers to a single country and usually includes only a limited number of models. Furthermore, papers differ in the size of the information set and the sample period.[1]

This paper is motivated by this gap in the empirical literature. We undertake a systematic comparison of a broad range of linear statistical models - eleven models in all - that have been applied in the recent literature. To improve comparability and robustness, we include five countries (Germany, France, Italy, Spain and the Netherlands) and the euro area in our analysis, utilizing the same information set across countries and the euro area. Moreover, our sample includes the volatile episode of the financial crisis of 2008 and its aftermath, which may make it easier to discriminate between the various models. We contrast the models' forecasting abilities before 2008 and that during the crisis period. This may be of great interest to policy makers, financial analysts and economic agents alike, as information on where the economy stands and where it is heading in the immediate short run is particularly valuable in times of great uncertainty.

Providing cross-country evidence on the relative performance of eleven different statistical forecasting models is our first contribution to the literature. Model forecasts are the result of purely mechanical recipes and do not incorporate subjective elements. Our second contribution concerns the potential usefulness of forecasts made by professional analysts (published by Consensus Forecasts on a quarterly basis). From a practical point of view, such forecasts are very cheap and easy to use. Moreover, they may, as expression of the "wisdom of the crowd", reflect much more information than the statistical information set, which is inevitably limited. A questionnaire by the European Central Bank (ECB) among the participants of the ECB Survey of Professional Forecasters found that the panelists regard forty percent of their short-term GDP forecasts to be judgment-based (ECB, 2009). We investigate for our sample to what extent subjective forecasts by analysts contain information beyond that generated by the best mechanical statistical model.

The remainder of the paper is structured as follows. Section 2 describes the statistical models and discusses how they deal with the challenges posed by large and irregularly shaped datasets. Section 3 describes the data, our pseudo real-time forecast design and other specification issues. Section 4 and Section 5 present the results for the mechanical models and the professional

[1] Rünstler *et al.* (2009) is an important exception, comparing three factor models, a bridge model and a quarterly VAR model for ten European countries, but this study does not include the financial crisis. Kuzin *et al.* (2012) analyzed the relative forecasting performance of MIDAS models versus dynamic factor models, including part of the crisis years (2008-2009). Liebermann (2012) analyzed the relative forecasting performance during the years 2001-2011, of a range of models, but only for the United States

forecasts, respectively. Section 6 summarizes our findings and concludes.

2 Linear statistical models for short-term GDP forecasting

2.1 Overview

Taking advantage of auxiliary information for forecasting of real GDP in the immediate short run in practice poses several challenges. The first challenge is posed by the large size of the information set. There are countless potentially useful variables for forecasting GDP. The size of the datasets in the empirical literature varies from 70 to more than 300 variables. The second problem relates to the fact that indicator variables are more frequently (monthly, weekly, daily) observed than GDP. Moreover, the dating of the most recent observation may vary across indicators because of differences in publication lags. This is known as the "ragged edge" problem, see Wallis (1986). The various statistical approaches in the literature deal with these challenges in different ways. To facilitate the discussion, Figure 1 depicts a schematic representation of the process of translating a large dataset into a single final GDP forecast along with several crucial modeling choices. Figure 1 shows that a forecasting procedure involves two transformations of

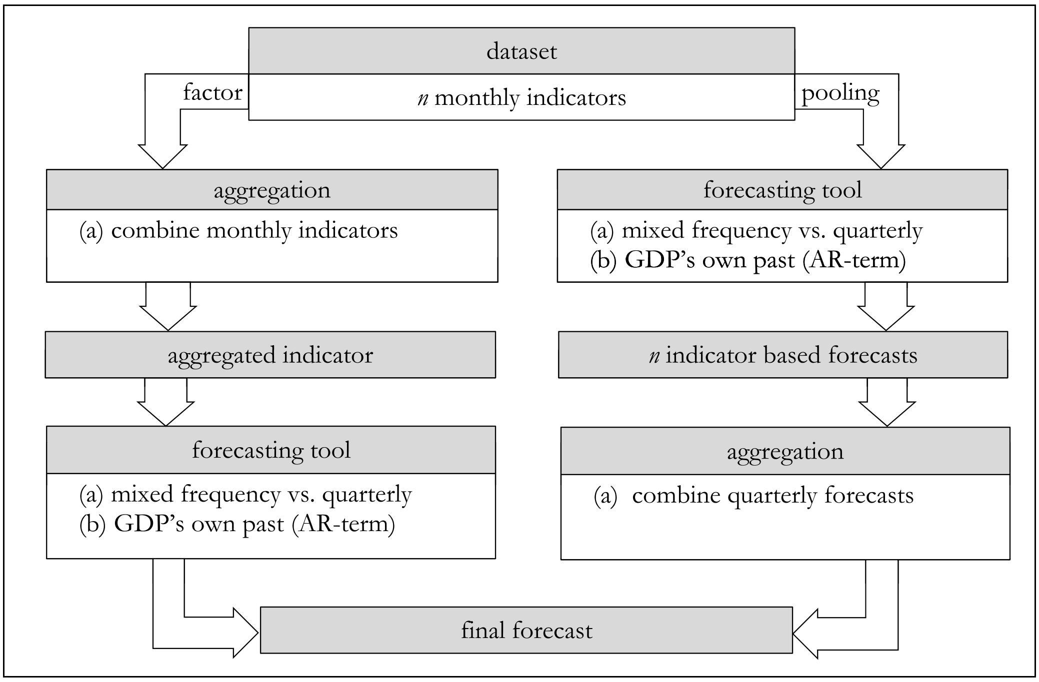


Figure 1: Schematic representation linear models for short-term GDP forecasting

the dataset of indicators to produce a final forecast: an aggregation and the application of a forecasting tool, which links auxiliary variables to real GDP growth. The two transformations can be executed in a different order, representing two fundamentally different strategies. The "factor strategy" takes the aggregation step first by summarizing the large dataset by a small number of series. This strategy exploits the fact that the auxiliary variables are correlated. Factor analysis is used to replace a large number of correlated time series by a limited number of uncorrelated (unobserved) factors or principal components representing the common information component of the original data series. The implicit weights (factor loadings) are determined by the correlation patterns in the original dataset. The factors serve as input for the forecasting procedure in the next step. Examples of this modeling strategy are static and dynamic factor

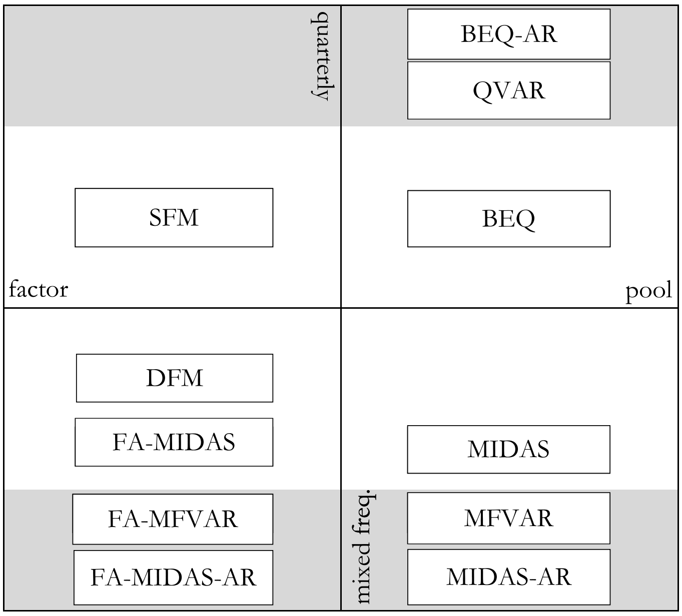


Figure 2: Schematic representation linear models for short-term GDP forecasting

models. By contrast, the second strategy first computes for each variable an indicator-specific GDP forecast, which are then aggregated into a single final forecast in the second step. We call this strategy the "pooling strategy" as it combines a large number of individual indicator-based forecasts. In this approach it is necessary to specify the weighting scheme of the individual forecasts. A simple scheme is the simple average, which gives each forecast an equal weight, but weights may also be recursively computed depending on the indicators' (recent) forecasting performance. Examples of the pooling strategy are bridge equations and VAR models.

The specification of the forecasting tool is the second distinguishing feature of the approaches. The traditional approaches, such as the bridge models and VAR models, rely on forecasting equations that are solely cast in quarterly terms. That means that monthly indicator variables first have to be aggregated to quarterly averages, before they can be used for forecasting. As this may not be an efficient use of the available information, recently developed approaches accommodate both quarterly and monthly data within the same equation or system of equations. These approaches take publication lags into account. The mixed-frequency VAR (MFVAR) model treats GDP as an unobserved monthly variable in a state-space framework. Monthly GDP is related to quarterly GDP via an identity. The quarterly GDP growth rate is only observed in the third month of every quarter. The mixed-data sampling (MIDAS) design relates quarterly GDP directly to a large number of lags of monthly data series using a parsimonious specification of the lag structure.

A third, more practical, specification issue is whether or not to include GDP's own past in the forecasting tool. In general, forecasting equations can easily be augmented by auto-regressive (AR) terms. Several authors have found that the AR-versions of models tend to result in modest improvements of forecasting performance (e.g. Foroni and Marcellino, 2012).

In this paper we analyze eleven statistical models. They are denoted as follows: (1) bridge model (BEQ), (2) BEQ with AR terms (BEQ-AR), (3) quarterly VAR model (QVAR), (4) diffusion index or static factor model (SFM), (5) dynamic factor model (DFM), (6) mixed-frequency VAR model (MFVAR), (7) factor-augmented MFVAR (FA-MFVAR), (8) mixed-data-sampling model (MIDAS), (9) MIDAS with AR terms (MIDAS-AR), (10) factor-augmented MIDAS (FA-MIDAS) and (11) FA-MIDAS with AR terms (FA-MIDAS-AR). Figure 2 classifies the eleven models according to the choices made on the three issues discussed above. The horizontal axis puts factor strategies versus pooling strategies. The vertical axis puts purely quarterly forecasting equations versus forecasting models that combine monthly and quarterly data (labeled mixed frequency). Finally, shaded areas signify models that include GDP's own past in the forecasting equation or system.

The next three subsections briefly discuss the forecasting models depicted in Figure 2, starting with the quarterly models. To improve the flow of the discussion we skip a number of issues in this section. We discuss the selection of the weighting scheme for indicator-based forecasts in Section 3.3 and the selection of lag orders and the number of common factors in Section 3.4. Moreover, we have moved some technical details to Appendix A.2.

We first clarify our notation. Below, $t = 1, \ldots, T$ stands for a monthly time index. The complete list of monthly indicators (indexed by $i = 1, \ldots, n$) is denoted as $x_t = (x_{1,t}, x_{2,t}, \ldots, x_{n,t})$. Following the usual convention quarterly GDP is only observed in the third month of each quarter, and has a quarterly frequency, defined as y_t^Q. Formally: $y_t^Q = \frac{1}{3}(y_{3k} + y_{3k-1} + y_{3k-2}), k = 1, 2, \ldots [T, 3]$,where y_{3k} is observed and y_{3k-1} and y_{3k-2} are unobserved 3-month GDP growth rates, i.e. growth rates vis-à-vis the same month of the previous quarter. Accordingly, the monthly series x_t have been transformed as 3-month growth rates or differences. The complete list of monthly indicators aggregated to quarterly level is defined as $x_t^Q = (x_{1,t}^Q, x_{2,t}^Q, \ldots, x_{n,t}^Q)$. The quarterly GDP growth forecast for quarter $t + h$ at time t is denoted as $y_{t+h|t}^Q$.

2.2 Quarterly models for GDP growth

2.2.1 Bridge equation (BEQ)

The quarterly bridge equation is a widely used method for forecasting GDP using monthly indicators; for applications see Kitchen and Monaco (2003) and Baffigi *et al.* (2004). Bridge equations are linear regressions that "bridge" monthly variables, such as industrial confidence and retail sales, to quarterly real GDP. Usually the monthly indicators are not known over the entire projection horizon. Following the literature, we proceed in two steps. Firstly, we obtain predictions of the necessary monthly values of indicator x_i over the forecasting horizon with help of univariate autoregressive models and aggregate these to appropriate quarterly values x_i^Q. Secondly, we use these quarterly aggregates to predict GDP. The bridge model for $x_{i,t}$ is:

$$y_t^Q = \alpha_i + \sum_{s=0}^{p_i} \beta_{i,s} x_{i,t-s}^Q + \varepsilon_{i,t}^Q, \qquad \varepsilon_{i,t}^Q \sim N(0, \sigma_{\varepsilon^Q}^2) \tag{1}$$

where α_i is a constant, p denotes the number of lags in the bridge equation and ε_i^Q is a normally distributed error-term. We estimate equation 1 for each of the n indicators, and then calculate the final forecast by weighting the n indicator-specific forecasts for each horizon.

2.2.2 Vector autoregressive model (QVAR)

The VAR approach is very similar to the bridge equation approach. Unlike bridge equations, VAR models use the information content of GDP itself to produce forecasts of GDP (e.g. Camba-

Mendez *et al.*, 2001). Moreover, it is a system approach, attempting to exploit the interdependence of indicator and real GDP dynamics. However, misspecification anywhere in the system may affect the accuracy of the GDP predictions. Being constrained to the quarterly time frame, the VAR model only uses information that corresponds to a full quarter. We estimate n quarterly bivariate VAR models that include one of the indicators and GDP growth:

$$z_{i,t}^Q = \alpha + \sum_{s=1}^{p_i} A_s z_{i,t-s}^Q + \varepsilon_{i,t}^Q, \qquad \varepsilon_{i,t}^Q \sim N(0, \Sigma_{\varepsilon^Q}) \tag{2}$$

where $z_{i,t}^Q = (y_t^Q, x_{i,t}^Q)'$. From each VAR we obtain an indicator-specific GDP forecast $y_{t+h|t}^Q$. As in the case of the bridge model, we form the final forecast as a weighted average of the individual forecasts.

2.2.3 Static Factor Model (SFM)

Factor models summarize the information of the dataset in a limited number of factors. Diffusion indices, introduced by Stock and Watson (2002), belong to the simplest versions of factor models as the factor dynamics are not explicitly modeled. We compute the GDP forecasts in two steps. The first step consists of the factor extraction procedure of Marcellino and Schumacher (2010). This gives estimates of the r common *static factors* $f_t = (f_{1,t}, f_{2,t}, \ldots, f_{r,t})$ of x_t, where $r << n$. Formally:

$$x_t = \Lambda f_t + \xi_t, \qquad \xi_t \sim N(0, \Sigma_\xi) \tag{3}$$

which relates the $n \times 1$ vector of monthly observations x_t to the monthly factors f_t via a matrix of factor loadings Λ and an idiosyncratic component $\xi_t = \xi_{1,t}, \ldots, \xi_{n,t}$. In the second step the monthly factors f_t are aggregated to quarterly values f_t^Q and the GDP forecasts for various horizons h are derived from the "leading" indicator regression:

$$y_{t+h|t}^Q = \mu + \beta' f_t^Q + \varepsilon_t \tag{4}$$

Note that in this equation GDP appears with a lead of h quarters. Hence, the h-step ahead forecast $y_{t+h|t}^Q = \beta' f_t^Q$ is found directly and there is no need to forecast the monthly variables.

2.3 Mixed frequency models

In recent years interest in mixed frequency models has increased among academics and policy makers because of the general failure of simple quarterly models to predict or signal the sharp downturn of the economy at the onset of the financial crisis.

2.3.1 Dynamic factor model (DFM)

Dynamic factor models are related to the static factor model. Apart from accounting for dynamics in factors, the key feature of this approach is the use of the Kalman filter, which allows for an efficient handling of the unbalancedness of the dataset and the different frequencies of the data. The Kalman filter replaces any missing monthly indicator observations with optimal predictions and also generates estimates of unobserved monthly real GDP subject to a temporal aggregation constraint for the quarterly observation. The dynamic factor model approach has been shown to provide relatively accurate forecasts for the United States (Giannone *et al.*, 2008), the euro area (see Bańbura *et al.*, 2011; Rünstler *et al.*,2009), Spain (Camacho and Perez-Quiros, 2010) and the Netherlands (den Reijer, 2012). In this paper we analyze the dynamic factor model proposed by Bańbura and Rünstler (2011), which is used by several central banks within the euro area.

The first equation of the model is the same as equation 3 of the static factor model and describes the r static factors of the matrix of indicators x_t. However, the DFM assumes that the idiosyncratic components are a multivariate white noise process, so that the covariance matrix Σ_ξ is a diagonal matrix rather than a full symmetric matrix. Furthermore, the DFM assumes that the factors follow a vector autoregressive process of order p:

$$f_t = \sum_{s=1}^{p} A_s f_{t-s} + \zeta_t, , \qquad \zeta_t \sim (0, \Sigma_\zeta) \tag{5}$$

where A is a square $r \times r$ matrix. Moreover, the covariance matrix of the VAR (σ_ζ) is driven by a q dimensional standardized white noise process η_t:

$$\zeta_t = B\eta_t, \qquad \eta_t \sim N(0, I_q) \tag{6}$$

where B is a $r \times q$ matrix. The final equation is a forecasting equation linking the factors to (unobserved) mean-adjusted real GDP growth:

$$y_t = \beta' f_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{7}$$

where y_t denotes the unobserved monthly GDP growth rate. The model is estimated in four steps. In the first step we obtain the factors loadings Λ and the estimated static factors $\hat{f}_t$ as described in Section 2.2.3. In the second step we estimate the coefficient matrices A_s in equation 5 and β in equation 7 by Ordinary Least Squares using $\hat{f}_t$. In the third step, we compute the covariance matrix σ_ζ and decompose it, obtaining an estimate of the matrix B. In the final step, we cast the model in state space and use the Kalman filter and smoother to re-estimate the estimated factors ($\hat{f}_t$) and monthly GDP growth. The state-space setup of our dynamic factor model is outlined in Section A.2.2. See Bańbura and Rünstler (2011) for a more elaborate description of the dynamic factor model and the estimation procedure.[2]

2.3.2 Mixed frequency vector autoregressive model (MFVAR)

Mixed Frequency VAR models (MFVAR) are VAR models that allow for data series with different frequencies. In contrast to the quarterly VAR model, the MFVAR model fully exploits all available monthly information. It shares with QVAR model the strengths and weaknesses of a system approach. In our case we focus on bivariate MFVAR models featuring a monthly indicator, unobserved monthly GDP and a temporal aggregation scheme.

Let $z_{i,t} = (y_t, x_{i,t})'$ be the vector of latent monthly real GDP and indicator $x_{i,t}$. The vector follows a VAR model:

$$z_{i,t} - \mu_{z_i} = \sum_{s=1}^{p} A_s(z_{i,t-s} - \mu_{z_i}) + \varepsilon_{i,t}, \qquad \varepsilon_{i,t} \sim N(0, \Sigma_\varepsilon) \tag{8}$$

where μ denotes the expectation of the corresponding variable. As documented by Kuzin *et al.* (2011) the means μ_{z_i} are often quite difficult to estimate. Therefore, we work with demeaned

[2] See Durbin and Koopman (2001) for a treatment of state space models and the use of the Kalman filter and smoother.

GDP and monthly indicators in the estimation procedure, adding the mean back afterwards to arrive at the final indicator-based forecast. As in the dynamic factor model, the Kalman filter and smoother fills in any missing monthly indicator observations with optimal predictions and estimates unobserved monthly real GDP subject to a temporal aggregation constraint for the quarterly observation. The state-space setup of the MFVAR is outlined in Section A.2.1. We estimate the model by the expectation-maximization algorithm as detailed in Mariano and Murasawa (2010).[3] As in the case of the QVAR model, we form the final GDP forecast as a weighted average of the individual forecasts derived from the n bivariate MFVAR models.

2.3.3 Mixed data sampling regression model (MIDAS)

The Mixed-Data Sampling Model (MIDAS) is a single horizon-specific equation that relates quarterly GDP to (various lags of) a monthly indicator (Ghysels *et al.*, 2007). It generates the GDP forecast in a direct way. The MIDAS model circumvents the ragged edge problem by including as regressors a fixed (fairly large) number of the most recent lagged values of the indicator. In applied work, the MIDAS model economizes on the number of parameters to be estimated by adopting a parsimoniously parameterized lag polynomial. The efficiency gains of such an approach come at the cost of potential efficiency losses if the implied restrictions on the lag structure between the monthly indicator and quarterly real GDP happen to be invalid. We follow Kuzin *et al.*(2011) in working with the exponential Almon lag polynomial. Our version of the indicator-specific MIDAS model for forecasting horizon h is defined by the following equations:

$$y^Q_{t+h} = \beta_0 + \beta_1 B(L^{(1/3)};\theta)x^{(3)}_{i,t+w} + \varepsilon_{i,t+h} \tag{9}$$

$$B(L^{(1/3)};\theta) = \sum_{k=0}^{K} c(k,\theta)L^{k/3} \tag{10}$$

$$c(k,\theta) = \frac{\exp(\theta_1 k + \theta_2 k^2)}{\sum_{k=0}^{K}\exp(\theta_1 k + \theta_2 k^2)} \tag{11}$$

where w is the time gap between the latest available observations of x_t and y^Q_t[4] $x^{(3)}_t$ is skipped from the monthly observations x_t. Every third observation, starting from the tth, one is included in the regressor $x^{(3)}_t$; thus, $x^{(3)}_{i,t} = x_{i,t} \forall t = \ldots, T-6, T-3, T$. Equation 10 describes a weighting function of lagged values with $L^{k/3}x^{(3)}_{i,t-1} = x^{(3)}_{i,t-1-k/3}$ representing a fractional lag operator. Equation 11 specifies the weight for lag k as a function of k and the two parameters governing the exponential Almon lag polynomial,[5] K is fixed at 12. The model's parameters $(\theta_1, \theta_2, \beta_0, \beta_1)$ are estimated by Nonlinear Least Squares, subject to $\theta_1 < 5$ and $\theta_2 < 0$. We compute the final GDP forecast as a weighted average of the individual forecasts derived from the n indicator specific MIDAS models.

[3] Another possibility would be to estimate the model by maximum likelihood, but we found this method had problems finding an optimal solution, especially for higher lag orders.

[4] The last period of y^Q_t is transformed to the corresponding monthly period.

[5] We also compared this lag polynomial to the recently proposed unrestricted lag polynomial (Marcellino and Schumacher, 2010), but the latter turned out to produce higher RMSFEs for the euro area and most countries in our sample. Details are available from the authors upon request.

2.4 Factor and AR augmented models

2.4.1 Factor augmented models

We consider versions of the MFVAR and MIDAS models in which the independent variable is a factor rather than an observed indicator. We denote these factor augmented versions by FA-MFVAR and FA-MIDAS, respectively. We restrict the analysis to a single factor. The first step of these procedures is the construction of the factor, which summarizes the monthly information set. It is no longer necessary to weight indicator-specific forecasts at the end to obtain the final GDP forecast. Equations 12 and 13 describe the FA-MFVAR model and the FA-MIDAS model for forecast horizon h, respectively:

$$z_t - \mu_z = \sum_{s=1}^{p} A_s(z_{t-s} - \mu_z) + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \Sigma_\varepsilon) \tag{12}$$

$$y^Q_{t+h} = \beta_0 + \beta_1 B(L^{(1/3)}; \theta)\hat{f}^{(3)}_{t+w} + \varepsilon_{t+h} \tag{13}$$

where $z_t = (y_t, f_t)'$. We calculate the factor as described in Section 2.2.3, applying the method proposed by Marcellino and Schumacher (2010).

2.4.2 AR augmented models

Finally, we consider versions of the BEQ, MIDAS and FA-MIDAS models that feature an AR(1) term as GDP's own past may contain important information. We denote these models by BEQ-AR, MIDAS-AR and FA-MIDAS-AR, respectively. The AR-BEQ model for x_i can be written as:

$$y^Q_t = \alpha + \varphi y^Q_{t-1} + \sum_{s=0}^{p_i} \beta_{i,s} x^Q_{i,t-s} + \varepsilon^Q_{i,t} \tag{14}$$

As proposed in Clements and Galvão (2008), the AR term is introduced as a common factor in the MIDAS-AR and FA-MIDAS-AR models:

$$y^Q_{t+h} = \beta_0 + \varphi y^Q_{t-1} + \beta_1 B(L^{(1/3)}; \theta)(1 - \varphi L^h)x^{(3)}_{i,t+w} + \varepsilon_{i,t+h} \tag{15}$$

$$y^Q_{t+h} = \beta_0 + \varphi y^Q_{t-1} + \beta_1 B(L^{(1/3)}; \theta)(1 - \varphi L^h)\hat{f}^{(3)}_{t+w} + \varepsilon_{t+h} \tag{16}$$

The parameter φ is estimated simultaneously with the other parameters.

3 Data, forecast design and specification issues

This section describes the dataset, the pseudo real-time setup, the weighting scheme we used for pooling the QVAR, BEQ, BEQ-AR, MFVAR, MIDAS and MIDAS-AR model forecasts and the selection of the number of lags and factors in the models.

3.1 Dataset

Our monthly dataset consists of 72 monthly time-series variables, using harmonized definitions across the countries. The indicator variables fall into four groups: production & sales, prices, monetary & financial indicators and surveys. Moreover, we added three composite indicators from the OECD.[6] Table VI in the appendix provides an overview of all variables, the applied transformations and the starting date of the monthly series for each country in our sample. Monthly data are usually available on a seasonally (and calendar effects) adjusted basis at the source. When necessary, raw data series are seasonally adjusted by the US Census X12-method. All monthly series are made stationary by differencing or log-differencing (in case of trending data, such as industrial production, retail sales and monetary aggregates). All variables are standardized by subtracting the mean and dividing by the standard deviation. This normalization is necessary to avoid overweighting of large variance series in the determination of common factors.

Quarterly GDP data for France, Italy, the Netherlands and Spain were taken from the OECD release data and revisions database.[7] Quarterly GDP data for Germany were taken from the Deutsche Bundesbank. Data refer to re-unified Germany from 1991.I onwards and to West Germany before 1991.I.[8] We constructed a synthetic GDP series for the euro area using the database underlying the ECB's Area-Wide Model, supplemented with data from the OECD database.[9]

3.2 Pseudo real-time design

The forecast design aims to replicate the availability of the data at the time forecasts are made in order to mimic the real-time flow of information as closely as possible. To this end, we used a data set downloaded on January 16, 2012 and combined this with the typical data release calendar to reconstruct the available dataset on the 16^{th} of each month during the period July 1995 - January 2012. All monthly indicator series start in January 1985, while the quarterly GDP series start in 1985.I. We thus employ a pseudo real-time design, which takes data publication delays into account, but ignores the possibility of data revisions for GDP and some indicators, such as industrial production. The latter implies that we might overestimate the forecasting accuracy of statistical models. However, the effects of data revisions on the final forecast may largely cancel out, since statistical methods typically attempt to eliminate noise in the process by either extracting factors from a large data set or pooling a large number of indicator-based forecasts. For example, Schumacher and Breitung (2008), using real-time data vintages for Germany, did not find a clear impact of data revisions on the forecast errors of factor models. Moreover, the effect on the relative performance of models, which is the main focus of this paper, is likely to be quite small (see also Bernanke and Boivin 2003). Abstracting from data revisions may affect the comparison of mechanical forecasts and forecasts by professional analysts to a greater extent, because GDP data are subject to substantial revisions. However, there is no obvious, feasible way to account for this.

[6] The primary source of the data is the ECB Statistical Datawarehouse (see `http://sdw.ecb.europa.eu/`). World trade and world industrial production are from the CPB World trade monitor (see `http://www.cpb.nl/en/world-trade-monitor`). Commodity price and most financial market indicators were taken from Thomson Reuters Datastream and most of the survey data from the European Commission (see `http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm`).

[7] The OECD release data and revisions database is publicly available at `http://stats.oecd.org/mei/default.asp?rev=1`. For France we used the January 2012 vintage, for Italy the January 2012, December 2011 and April 2006 vintages, for the Netherlands the January 2012 and July 2005 vintages and for Spain the January 2012, November 2011, May 2005 and January 1999 vintages. The series for Italy, the Netherlands and Spain were constructed by backdating the January 2012 GDP-series by applying the quarter-on-quarter growth rates from the most recent GDP vintage.

[8] See `http://www.bundesbank.de/statistik/statistik_zeitreihen.en.php?lang=en&open=&func=row&tr=JB5000`.

[9] See `http://www.eabcn.org/data/awm/index.htm`.

Table I: Timing of forecast exercise (example: forecast for third quarter)

Nr.	Quarter to be forecast	Month	Forecast made in middle of
1	Two-quarter ahead	1	January
2		2	February
3		3	March
4	One-quarter ahead	1	April
5		2	May
6		3	June
7	Nowcast	1	July
8		2	August
9		3	September
10	Backcast	1	October
11		2	November

We estimate the parameters of all models recursively, using only the information available at the time of the forecast. See Rünstler *et al.* (2009), Giannone *et al.* (2008) and Kuzin *et al.* (2011), among others, for a similar approach. We construct a sequence of eleven forecasts for GDP growth in a given quarter, obtained in consecutive months. Table I explains the timing of the forecasting exercise, taking the forecast for the third quarter of 2011 as an example. We make the first forecast in January 2011, which is called the two-quarter-ahead forecast in month one. We subsequently produce a monthly forecast for the next ten months through November. The last forecast is made just before the first release of GDP in mid-November. Following the conventional terminology, *forecasts* refer to one or two-quarter ahead forecasts, *nowcasts* refer to current quarter forecasts and *backcasts* refer to forecasts for the preceding quarter, as long as official GDP figures are not yet available. In case of our example 2011.III, we make two-quarter ahead forecasts from January to March, one-quarter ahead forecasts from April to June, nowcasts from July to September, and backcasts in October and November.

3.3 Weighting scheme of indicator-based forecasts

The models BEQ, BEQ-AR, QVAR, MFVAR, MIDAS and MIDAS-AR construct a large number of different indicator-specific forecasts in the first stage, which have to be aggregated in the second stage to obtain the final forecast. Taking a weighted average of a large number of forecasts may ameliorate the effects of misspecification bias, parameter instability and measurement errors in the data, that may afflict the individual forecasts (Timmerman 2006). We have investigated three different weighting schemes: (i) equal weights (simple mean); (ii) weights that are inversely proportional to the Root Mean Squared Forecast Error (RMSFE) measured from the start of the sample period until the previous quarter (recursive RMSFE scheme); and (iii) weights that are inversely proportional to the RMSFE measured over the past four quarters (moving window RMSFE scheme). Equal weights have been proven to work quite well as pooling mechanism (e.g. Stock and Watson, 2004 and Clark and McCracken, 2010). The latter two methods assign weights to the indicators based on their forecasting performance in the (recent) past.

Tables VII - in XII in the Appendix give an overview of the RMSFE of the three weighting schemes by horizon and country for the six relevant models. The overall picture is that the moving window RMSFE weighting scheme, which emphasizes performance in the recent past, has the smallest RMSFE on average, although the difference with the recursive RMSFE weighting scheme is quite small. In the rest of the paper we therefore apply the moving window RMSFE weighting scheme for all relevant models and all countries.

3.4 Selection of maximum number of lags and number of common factors

Across models, countries and samples, the maximum number of lags in forecasting equations is determined recursively by the Schwartz information criterion (SIC). The maximum number of lags is 4 for quarterly data and 12 for monthly data.[10]

Estimation of the static and dynamic factor model requires the specification of the number of static and dynamic common factors, denoted by r and q respectively. We base the choice of r and q on the combination that minimizes the RMSFE, evaluated over the entire sample 1996.I-2011.III.[11] We limited the search for r to the interval $[1, 6]$. The upper bound of 6 was derived from the scree test of Cattell (1966). A grid search resulted in the following number of static factors: euro area: $r = 2$; Germany: $r = 1$; France: $r = 3$; Italy: $r = 4$; Spain: $r = 3$; Netherlands: $r = 6$.

We followed a similar procedure for the selection of the value of r and q in the dynamic factor model, imposing the restrictions $r \leq 6$ and $q \leq r$. The second restriction is motivated by the finding of D'Agostino and Giannone (2012) that restricting the number of dynamic factors to be smaller than the number of static factors does not hurt predictive power. The specification search led to the following numerical values: euro area: $r = 6$, $q = 5$, $p = 4$; Germany: $r = 2$, $q = 2$, $p = 3$; France: $r = 5$, $q = 2$, $p = 6$; Italy: $r = 6$, $q = 4$, $p = 2$; Spain: $r = 6$, $q = 2$, $p = 5$; Netherlands: $r = 6$, $q = 4$, $p = 2$.

4 Empirical results for statistical models

4.1 Forecasting performance

Table II presents data on the forecast performance of the eleven statistical models for our five countries and the euro area for the complete sample period 1996.I-2011.III (63 quarters). The underlying empirical analysis has been carried out on a monthly basis for eleven horizons. To save space Table II (and the other tables in this paper as well) reports results for the two and one-quarter ahead forecasts, the nowcast and the backcast, which have been calculated as the average of the corresponding monthly data. We measure forecast performance by the root mean square forecast error (RMSFE). The first column of Table II reports the RMSFE of the benchmark model (AR model). For the other statistical models the entries refer to their RMSFE relative to that of the benchmark model in order to improve the comparability of the results across countries and horizons. Shaded entries indicate the model with the lowest RMSFE in a row (for a particular horizon). Bold faced entries indicated models that have an RMSFE that is less than 10 per cent larger than that of the best model and also smaller than the RMSFE

[10] For the MFVAR model we set the maximum number of lags equal to 3, as a ceiling of 4 produced unstable results. Moreover, for the dynamic factor model the ceiling is set at 6 in Equation 5. Detailed results are available from the authors upon request.

[11] Alternatively one could choose the number of factors r and q on the basis of in-sample criteria, as described in Bai and Ng (2002,2007). Our experience, like that of Bańbura and Rünstler (2011), is that these criteria tend to indicate a relatively large number of factors, leading to volatile and less accurate forecasts. Detailed results are available from the authors upon request.

Table II: Forecasting performance statistical models (RMSFE), 1996.I-2011.III

Frequency	Quarterly					Mixed frequency						
Pool/Factor	Benchmark	Pooling			Factor	Factor	Pooling					
Model	AR	BEQ	BEQ-AR	QVAR	SFM	DFM	MIDAS	FA-MIDAS	MIDAS-AR	FA-MIDAS-AR	MFVAR	FA-MFVAR
RMSFE	(Absolute)	(Relative to AR-model)										
Euro area												
2Q ahead	*0.64*	**0.96**	**0.97**	1.01	0.95	1.01	**0.97**	1.00	**0.97**	1.01	**0.97**	1.08
1Q ahead	*0.63*	**0.90**	**0.91**	1.00	0.83	**0.88**	0.92	0.98	0.93	0.97	0.92	0.99
nowcast	*0.60*	0.85	0.83	0.96	0.67	**0.68**	0.88	0.82	0.83	0.80	0.89	0.78
backcast	*0.53*	0.87	0.81	0.92	**0.61**	0.56	0.83	0.72	0.73	0.70	0.87	0.66
Germany												
2Q ahead	*0.96*	**0.94**	**0.94**	**0.96**	0.92	**0.93**	**0.94**	**0.98**	**0.98**	**1.00**	**0.94**	1.01
1Q ahead	*0.94*	**0.93**	**0.93**	0.97	**0.87**	0.85	0.93	0.97	0.94	0.97	0.94	0.98
nowcast	*0.93*	0.90	0.88	0.97	**0.77**	0.72	0.89	0.84	0.90	0.84	0.92	0.84
backcast	0.93	0.83	0.83	0.94	**0.73**	0.66	0.78	**0.71**	0.81	0.74	0.91	0.74
France												
2Q ahead	*0.54*	**0.95**	**0.95**	**0.99**	**0.94**	0.92	**0.94**	**1.00**	**0.95**	1.01	**0.94**	1.11
1Q ahead	*0.52*	0.92	0.91	1.01	0.80	**0.84**	0.94	0.97	0.92	0.95	0.92	1.02
nowcast	*0.47*	0.90	0.87	0.98	**0.75**	0.69	0.93	0.89	0.88	0.84	0.86	0.90
backcast	*0.44*	0.90	0.87	0.95	0.63	**0.64**	0.91	0.72	0.85	0.75	0.89	0.76
Italy												
2Q ahead	*0.78*	**0.95**	**0.95**	**0.97**	0.94	**0.96**	**0.94**	**0.96**	**0.95**	**0.96**	**0.95**	1.01
1Q ahead	*0.73*	**0.97**	**0.98**	1.01	0.89	**0.93**	**0.98**	1.01	**0.97**	1.00	0.98	1.05
nowcast	*0.70*	0.92	0.91	0.99	**0.76**	0.72	0.94	0.86	0.92	0.85	0.92	0.86
backcast	*0.68*	0.90	0.87	0.92	0.64	**0.65**	0.90	0.73	0.87	0.72	0.87	0.73
Spain												
2Q ahead	*0.58*	**0.98**	1.00	1.00	**0.94**	0.89	1.00	1.01	0.98	1.02	1.02	1.03
1Q ahead	*0.52*	1.02	1.02	1.03	**0.86**	0.80	1.04	1.06	0.94	0.97	1.14	1.06
nowcast	*0.46*	1.01	1.05	1.01	0.87	0.72	1.01	1.04	0.91	0.98	1.17	1.08
backcast	*0.49*	0.86	1.00	0.90	0.77	0.64	0.89	0.87	0.96	1.02	1.09	1.09
Netherlands												
2Q ahead	*0.71*	0.96	**0.97**	**1.00**	1.03	1.00	**0.97**	1.02	**0.97**	1.03	**0.98**	1.10
1Q ahead	*0.71*	0.91	0.91	0.99	0.81	**0.88**	0.95	0.98	0.92	0.98	0.96	1.02
nowcast	*0.68*	0.86	0.85	0.97	**0.74**	0.73	0.91	0.83	0.88	0.84	0.92	0.84
backcast	*0.64*	0.90	0.86	0.93	**0.71**	0.71	0.90	0.82	0.85	0.81	0.97	0.86

Notes: AR: Autoregressive model, BEQ: Bridge equation, BEQ-AR: Bridge equation with AR term, QVAR: Vector autoregressive models, SFM: Static Factor Model, DFM: Dynamic factor model, FA-MIDAS: Factor augmented MIDAS, FA-MIDAS-AR: Factor augmented MIDAS with AR term, MFVAR: Mixed frequency vector autoregressive model, FA-MFVAR: Factor augmented mixed frequency vector autoregressive model, MIDAS: Mixed data sampling model, MIDAS-AR: MIDAS with AR-term.

Grey cells indicate models with the lowest RMSFE. Figures in boldface indicate models whose RMSFE is at most 10% larger than the RMSFE of the best model.

of the benchmark model.[12] The 10 per cent threshold is meant as a rough assessment of the economic significance of differences in forecasting ability. We will call models that meet this condition "competitive models" as in terms of forecasting performance they do not differ "too much" from the best model.[13]

The outcomes in Table II point to several interesting results. First, incorporating monthly information in statistical forecasting procedures pays off in terms of forecasting accuracy, in particular for nowcasts and backcasts. The large majority of the relative RMSFEs are smaller than 1 and they also tend to fall if the horizon shortens and more monthly information is absorbed. Second, for many models the gain is rather limited when forecasting one and two-quarters ahead. For the two-quarter ahead forecast, the best models have on average an RMSFE that is only 5% lower than the benchmark. Except for Spain, even the best statistical model does not deliver an economically significant improvement. For the one-quarter ahead forecast the average improvement by the best models is 15% on the benchmark, but the other models generally post gains that are less than 10% on the benchmark. For the nowcast and backcast the average gain in accuracy is around a third for the best performing models. This pattern suggests that statistical models have greater value added when they can use information that pertains to the relevant quarter. Their relative strength is to improve the assessment of the current state of the economy. Third, the static and dynamic factor models display the best performance overall. Looking across countries and horizons, either the static or the dynamic factor model performs best. The only exception is the bridge model which is the best model in case of the two-quarter ahead forecast for the Netherlands. The dynamic factor model works better for nowcasts and backcasts, while the static factor model has the edge for the one-quarter ahead forecast. Fourth, many models are competitive at the two-quarter ahead horizon in most of the countries, but their number quickly falls as the horizon shortens. For the majority of the countries there typically is only one (other) competitive model for nowcasts and backcasts, usually the static or dynamic factor model. The first result is another piece of evidence that predictions by statistical models incorporate little information at the two-quarter ahead horizon. The second result suggests that the static and dynamic factor model display a significantly larger ability to absorb monthly information than the other models. Within the latter group, factor-augmented models (FA-MIDAS, FA-MIDAS-AR and FA-MFVAR) are the best of the rest, while the quarterly and MFVAR models are clear underperformers. Fifth, within our sample of countries Spain is an exceptional case as all statistical models do badly for all horizons, except for the static and dynamic factor model.

4.2 The marginal value of statistical models

Ranking models by their RMSFE gives a first perspective on their relative usefulness. This subsection focuses on the marginal value of models by investigating whether forecasts generated by different models differ in their information content. As the various statistical approaches follow different strategies of extracting monthly information, it is conceivable that some models are complementary. In that case taking a weighted average of their respective forecasts may improve forecast accuracy. Even a badly performing model may have a positive marginal value provided it is able to pick up specific useful information. We establish the marginal value of the models versus the best statistical model (lowest RMSFE) by running an encompassing test (see

[12] If the best model has an RMSFE of 0.6, the cut-off point is an RMSFE of 0.66.

[13] Like other authors we refrain from doing conventional statistical tests as these are not discriminating in practice.

for example Stekler, 1991 and Rünstler *et al.*, 2009). The test regression is:

$$y^Q_{t+h|t} = \lambda \hat{y}^Q_{\mathrm{a}(t+h|t)} + (1-\lambda)\hat{y}^Q_{\mathrm{b}(t+h|t)} + \varepsilon_t \qquad (17)$$

Where y^Q_t is GDP growth in t, $\hat{y}^Q_{\mathrm{a}(t+h|t)}$ and $\hat{y}^Q_{\mathrm{b}(t+h|t)}$ are the forecasts for quarter $t+h$ on time t of the alternative and best model respectively, λ is the weight of the alternative model and $(1-\lambda)$ is the weight of the best model. In order to get interpretable results, we impose the restriction that λ lies between 0 and 1. The alternative model contains additional information compared to the best model if $\lambda > 0$. We estimate λ and its standard error on the interval [0,1] by Maximum Likelihood (ML) and perform a one-sided (asymptotically valid) test of the hypothesis $\lambda = 0$ at the 5% level of significance. All calculations refer to the complete sample period 1996.I-2011.III (63 quarters).

Table III reports the results of our encompassing test. Entries depict the RMSFE of the forecast combination relative to the RMSFE of the best model as a measure of the potential gains from using forecast combinations. The estimated weight λ itself is not reported; entries in boldface signify λ estimates that are statistically greater than zero. A blank entry means that de ML algorithm returned the corner solution $\lambda = 0$.

The main message of Table III is that the gains from combining forecasts by different statistical models are limited in economic terms. Moreover, no model emerges as a clear winner, the best model in terms of marginal value is country-specific. It thus appears that the various approaches do not greatly differ with respect to the type of information they extract from large-scale monthly datasets. In the majority of the cases there is no gain in accuracy at all for horizons up to the nowcast. The best opportunities are for improving backcasts, when models have absorbed the maximum amount of monthly information. Except for Germany and Italy, the majority of the models offers some scope for improving backcasts. For the euro area the maximum possible reduction in the RMSFE is 9%, for France 4%, for Spain 9% and for the Netherlands 6%. For nowcasts the maximum reduction in the RMSFE does not exceed 4%. At the two-quarter ahead horizon a comparatively large number of models appear to offer additional information, but the associated gains are very small (typically 1% reduction in RMSFE). Finally, Table III shows that statistical significance and economic importance are different concepts. Most non-zero entries reflect a significant test result for the encompassing test, while most of the gains in forecast accuracy are very small.

4.3 Splitting the sample: Great Moderation versus Financial crisis

Our sample includes the financial crisis when real GDP went through a particularly volatile phase across the industrialized countries. An obvious question is whether and to what extent the performance of statistical forecasting models differs between the financial crisis period and the period before the financial crisis which was characterized by a large degree of macroeconomic stability. The latter period has been labeled as the Great Moderation. Most of the existing literature on short term forecasting is based on data from the Great Moderation period. Forecasting in volatile times poses of course greater challenges, so the results of a comparative analysis will be more informative on the issue which models are particularly apt at absorbing monthly information. Moreover, good forecasts and nowcasts are of greater importance to economic agents and policy makers in a volatile environment.

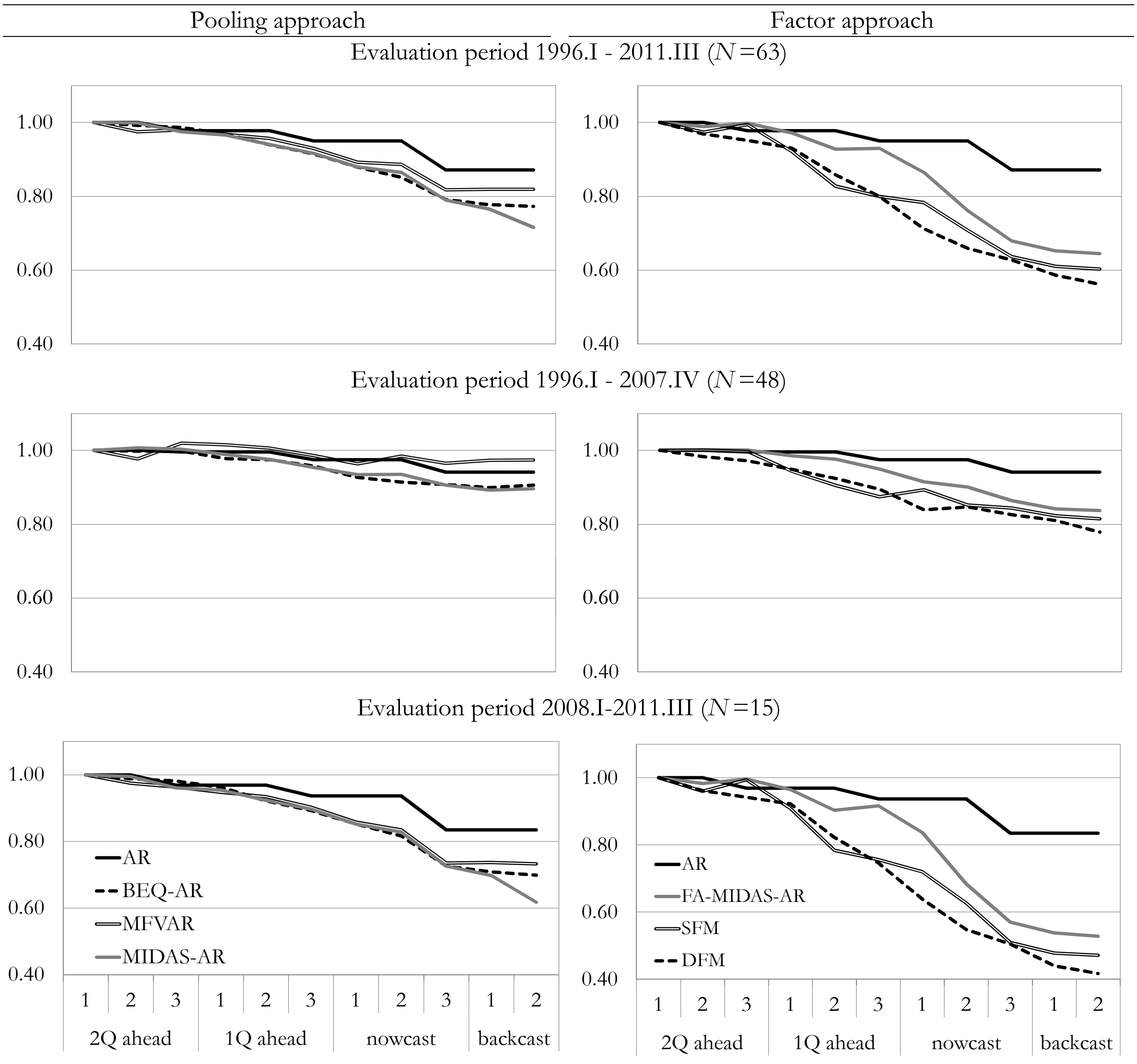
Table III: Marginal value of statistical models (evaluation period 1996.I-2011.III)

Frequency	Quarterly					Mixed frequency						
Pool/Factor	Benchmark	Pooling			Factor	Factor	Pooling					
Model	AR	BEQ	BEQ-AR	QVAR	SFM	DFM	MIDAS	FA-MIDAS	MIDAS-AR	FA-MIDAS-AR	MFVAR	FA-MFVAR
RMSFE	(RMSFE(combination of alternative and best model)/RMSFE(best model))											
Euro area												
2Q ahead	1.00	**0.99**	**0.99**	1.00	.	.	**0.99**	.	0.99	.	**0.99**	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	.	**0.96**	.	.	.	.	.	.
backcast	**0.98**	**0.97**	**0.97**	**0.97**	**0.96**	.	**0.96**	**0.96**	**0.94**	**0.96**	**0.98**	**0.91**
Germany												
2Q ahead	.	.	.	.	.	1.00	.	.	.	.	**0.99**	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	.	.	.	.	.	.	.	.
backcast	.	.	.	.	**0.99**	.	.	.	.	.	.	.
France												
2Q ahead	**0.99**	**0.99**	**0.99**	**0.99**	.	.	**0.98**	.	**0.98**	.	**0.98**	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	**0.99**	.	.	.	.	.	.	.
backcast	**0.99**	0.99	0.99	**0.98**	.	**0.96**	0.99	.	0.99	.	**0.99**	.
Italy												
2Q ahead	.	0.99	.	.	.	.	**0.99**	.	**0.99**	.	.	.
1Q ahead	**0.99**	.	.	.	.	.	1.00	.	**0.99**	.	.	.
nowcast	.	.	.	.	.	.	.	.	.	.	.	.
backcast	.	.	.	.	.	**0.98**	.	.	.	.	.	0.98
Spain												
2Q ahead	**0.97**	**0.99**	**0.99**	**0.98**	.	.	**0.98**	.	**0.98**	.	**0.99**	.
1Q ahead	**0.98**	.	1.00	**0.99**	**0.97**	.	.	.	**0.98**	.	.	.
nowcast	**0.96**	.	.	**0.99**	.	.	.	.	**0.99**	.	.	.
backcast	**0.91**	**0.98**	0.99	**0.95**	.	.	**0.98**	.	**0.99**	.	.	.
Netherlands												
2Q ahead	.	.	.	.	**0.99**	.	.	.	.	.	.	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	**0.96**	.	.	.	.	.	.	.
backcast	**0.96**	**0.95**	**0.94**	**0.95**	.	**0.96**	**0.95**	**0.97**	**0.95**	**0.96**	**0.95**	**0.96**

Notes: AR: Autoregressive model, BEQ: Bridge equation, BEQ-AR: Bridge equation with AR term, QVAR: Vector autoregressive model, SFM Static Factor Model, DFM: Dynamic factor model, FA-MIDAS: Factor augmented MIDAS model, FA-MIDAS-AR: Factor augmented MIDAS model with AR term, MFVAR: Mixed frequency vector autoregressive model, FA-MFVAR: Factor augmented mixed frequency vector autoregressive model, MIDAS: Mixed data sampling model, MIDAS-AR: MIDAS model with AR-term.

Grey cells indicate model with the lowest RMSFE. Figures in boldface indicate that the encompassing test is statistically significant at the 5% level.

We divide the sample period into two parts: 1996.I - 2007.IV (Great Moderation) and 2008.I - 2011.III (Financial crisis). We discuss the performance of the models on the basis of their learning curve, which shows the relative decline in the RMSFE as the forecasting horizon shortens, averaged over four countries and the euro area.[14] We calculate a model's learning curve as the RMSFE standardized by the RMSFE for the first month of the two-quarter ahead forecast. Figure 3 shows the learning curves of selected models for the complete sample period and the two subperiods (in the rows). The graphs on the left refer to models that aggregate indicator-specific forecasts, the graphs on the right refer to models that rely on factor analysis to summarize indicators. For presentational reasons we restrict the comparison to the AR versions of the MIDAS, BEQ and FA-MIDAS models (as they perform better than the non-AR versions) and leave out the QVAR and FA-MFVAR models because of their poor forecasting capabilities.



Notes: RMSFE 2Q ahead forecast=100; all lines excluding Spain.

Figure 3: Learning curve statistical models

[14] We leave out Spain, because all statistical models fail to beat the benchmark model in the period 1996.I-2007.IV. Country details can be found in Tables XIII-XVIin Appendix A.3 which are versions of Tables II and III for both subperiods.

For the complete sample period we find that the dynamic factor model displays the steepest learning curve, with the static factor model being a close second. In addition, models involving factor analysis have steeper learning curves than models that aggregate indicator-specific forecasts. This is a stable pattern that holds both during the Great Moderation episode and the crisis episode (and also across countries). It thus appears that the dynamic and static factor model are the fastest learning models in volatile as well as tranquil environments.

Predicting GDP is much more difficult in the crisis period. The RMSFE of the benchmark model during the crisis period is two to three times as large as that during the Great Moderation. Part of this deterioration can be offset as the scope for improving forecasts by utilizing monthly information appears to be larger in volatile times, in particular for nowcasting and backcasting. For example, the RMSFE of the dynamic factor model falls by 22% on average over the course of 11 months in the period before the crisis as compared to 58% in the crisis period. Differences in forecast accuracy across models are considerably larger after the crisis than before the crisis. This also means that the number of competitive models during the Great Moderation is much larger (about twice as many) than after the financial crisis, even for the nowcasting and backcasting horizons. This finding is consistent with the results of D'Agostino and Giannone (2012) who show that the gain from using factor models is substantial, especially in periods of high comovement, as was the case during the Financial crisis. The crisis episode poses a more demanding test to models and consequently fewer models manage to pass. This finding also implies that the cost of employing a suboptimal model has increased after the crisis. Finally, the potential gains of combining statistical models (marginal value) tend to be markedly smaller during de financial crisis compared to the preceding period.[15]

4.4 Assessing model features

The fact that our analysis includes eleven models five countries and the euro area allows us to shed some light on the issue which model features are especially valuable for forecasting and nowcasting. Referring to Figure 2, we focus on the following modeling choices: (1) employing factor analysis to summarize monthly information; (2) allowing for mixed frequencies in the forecasting equation or system; (3) exploiting GDP's own past by adding an autoregressive term to the forecasting equation. To assess a model feature's effect on the RMSFE we compare (sets of) models that only differ in that aspect. Moreover, we take the average over four countries and the euro area (once again we exclude Spain) to average out the country-specific component.

To measure the impact of utilizing factor analysis for aggregating monthly information rather than aggregating indicator-specific forecasts we can compare three pairs of models: (FA-MIDAS, MIDAS), (FA-MIDAS-AR, MIDAS-AR) and (FA-MFVAR, MFVAR). For the AR effect we can also exploit three pairs: (BEQ-AR, BEQ), (MIDAS-AR, MIDAS) and (FA-MIDAS-AR, FA-MIDAS). We assess the mixed frequency effect in two different ways. The first method involves the pairs (MIDAS, BEQ) and (MIDAS-AR, BEQ-AR), which relates quarterly GDP data on the left-hand side to monthly data (as opposed to quarterly averages of monthly data) on the right-hand side in a single forecasting equation setting. The second method is based on the pair (MFVAR, QVAR) and includes the effect of making GDP a monthly latent variable in a system.

Table IV reports the impacts of the three model features (averaged over four countries and the

[15] Moreover, the encompassing test is significant in only a few cases but this can partly be attributed to the low number of observations.

Table IV: Effects of model features on forecast accuracy

Model feature	AR				Mixed Frequency				Factor			
Model	FA-MIDAS-AR	MIDAS-AR	BEQ-AR	AR	MIDAS	MIDAS-AR	MF	MFVAR	FA-MFVAR	FA-MIDAS	FA-MIDAS-AR	Factor
Base model	FA-MIDAS	MIDAS	BEQ	Avg.	BEQ	BEQ-AR	Avg.	QVAR	MFVAR	MIDAS	MIDAS-AR	Avg.
Evaluation period 1996.I-2011.III												
2Q ahead	0.01	0.01	0.00	**0.01**	0.00	0.01	**0.00**	-0.03	0.11	0.04	0.04	**0.06**
1Q ahead	-0.01	-0.01	0.00	**-0.01**	0.02	0.01	**0.01**	-0.05	0.06	0.04	0.04	**0.05**
nowcast	-0.01	-0.03	-0.02	**-0.02**	0.03	0.01	**0.02**	-0.07	-0.06	-0.06	-0.05	**-0.06**
backcast	0.00	-0.04	-0.03	**-0.02**	-0.02	-0.03	**-0.02**	-0.03	-0.16	-0.12	-0.08	**-0.12**
Evaluation period 1996.I-2007.IV												
2Q ahead	0.00	0.01	0.00	**0.00**	-0.01	0.00	**0.00**	-0.02	0.04	0.04	0.03	**0.04**
1Q ahead	0.01	0.00	0.00	**0.00**	0.01	0.00	**0.00**	0.01	-0.01	0.02	0.03	**0.01**
nowcast	0.00	-0.02	-0.01	**-0.01**	0.01	0.01	**0.01**	0.00	-0.05	-0.03	0.00	**-0.03**
backcast	0.02	-0.01	0.01	**0.01**	0.00	-0.01	**0.00**	0.04	-0.09	-0.06	-0.03	**-0.06**
Evaluation period 2008.I-2011.III												
2Q ahead	0.02	0.01	0.00	**0.01**	0.00	0.01	**0.01**	-0.04	0.14	0.04	0.05	**0.08**
1Q ahead	-0.02	-0.01	0.00	**-0.01**	0.03	0.02	**0.02**	-0.08	0.10	0.05	0.04	**0.06**
nowcast	-0.03	-0.04	-0.02	**-0.03**	0.04	0.02	**0.03**	-0.11	-0.06	-0.09	-0.08	**-0.08**
backcast	-0.01	-0.07	-0.07	**-0.05**	-0.03	-0.03	**-0.03**	-0.07	-0.21	-0.18	-0.12	**-0.17**

Notes: Effects are calculated as (RMSFE(model) - RMSFE(base model))/RMSFE(base model) averaged across the euro area, Germany, France, Italy and the Netherlands.

AR: Autoregressive model, BEQ: Bridge equation, BEQ-AR: Bridge equation with AR term, QVAR: Vector-autoregressive models, FA-MIDAS: Factor augmented MIDAS, FA-MIDAS-AR: Factor augmented MIDAS with AR term, MFVAR: Mixed frequency vector-autoregressive model, FA-MFVAR: Factor augmented mixed frequency vector-autoregressive model, MIDAS: Mixed data sampling model, MIDAS-AR: MIDAS with AR-term.

euro area) for the complete sample period and the two subperiods. Starting with the effect of utilizing factor analysis, we find that this improves the accuracy of nowcasts and backcasts, but factor augmented models show a weaker performance when forecasting one or two-quarters ahead. This suggests that summarizing information of monthly data is primarily helpful when the information pertains to the quarter of interest itself. When forecasting one and two-quarters ahead the inevitable loss of information that summarizing implies appears to dominate any gains from the removal of noise. For the complete sample the average gain is 6% for nowcasts and 12% for backcasts. During tranquil times these gains are smaller, while in the crisis period the gains are larger, up to 17% for backcasts. Allowing for mixed frequencies in a single equation setting (MIDAS or BEQ) only modestly lowers the RMSFE for backcasts, while for the other horizons the RMSFE deteriorates slightly. In the crisis these effects are somewhat more pronounced, but still small. Treating GDP as monthly latent variable in a system has positive effects for all horizons for the whole sample, but this result appears to be completely driven by the crisis period. Lastly, exploiting GDP's own past by adding an AR term tends to improve the accuracy of forecasts a little bit for most horizons, especially for nowcasts (3%) and backcasts (5%) during the crisis episode.

5 Analysis of forecasts by professional analysts

The views of professional forecasters are an alternative and convenient source of information for policy makers and market participants. Currently, several surveys on the economic outlook exist and are regularly updated. The European Central Bank undertakes a quarterly survey among professional forecasters to get information on inflation expectations and growth prospects for the euro area. In the US, the Federal Reserve Bank of Philadelphia runs a well-known survey. Moreover, the private sector firm Consensus Economics collects and publishes economic forecasts on a monthly basis in the publication *Consensus Forecasts*. Consensus Forecasts offers an overview private analysts' expectations for a set of key macroeconomic variables for a broad range of countries. Consensus Forecasts is best known for its expectations on annual GDP growth for the current and next year. However, it also provides quarterly forecasts for GDP, which we will use in this paper.[16] The panelists supply their forecasts for six consecutive quarters, starting from the first unpublished quarter. The number of respondents varies somewhat over time, but on average about nine institutions participate in the poll for the Netherlands, fifteen for Italy and Spain, twenty for France and thirty for Germany and the euro area.

This section investigates two issues. The first issue is the quality of Consensus forecasts as a separate forecasting device compared to the best statistical model. The second issue is the marginal value of Consensus forecasts based on an encompassing test versus the best model. In forming their expectations, analysts include subjective assessments on potentially a multitude of relevant factors (alongside presumably model-based predictions). If a mixture of model-based and (subjective) Consensus forecasts improves the accuracy of forecasts, this can be viewed as evidence that forecasts by analysts indeed embody a different type of valuable information (subjective judgments).

We use the mean quarterly forecast as the measure of private sector expectations in our analysis. Fresh Consensus forecasts become available only once a quarter, in the second week of

[16] The annual Consensus forecasts have been analyzed in several papers (e.g. Ager *et al.* (2009), Batchelor (2001), Loungani and Rodriguez (2008) and Lahiri *et al.* (2006)). The quarterly forecasts have not been used before, except in a case study for the Netherlands by de Winter (2011).

the last month of the quarter. For the information set this means Consensus forecasts are not updated in the first and second month in a quarter, while monthly indicator series are updated every month. Moreover, at the time panelists form their expectations they have information on GDP growth in the preceding quarter. The backcast for quarter t is therefore equal to the non-updated Consensus forecast published in the last month of quarter t.

Table V presents the results for Consensus forecasts for five countries and the euro area for the complete sample period, the pre-crisis period and the crisis period.[17] For two-quarter ahead forecasts Consensus forecasts are better than the best statistical model in case of the euro area and Spain, while they are a competitive model in another three cases over the whole sample. When the horizon shortens, however, the relative performance versus the best model deteriorates starkly in the euro area and all countries except for Germany and Spain. Consequently, purely mechanical models seem to be (much) more adept at learning when monthly information becomes available. In the relatively stable pre-crisis period, Consensus forecasts fare very poorly, usually ranking at the bottom of the list. However, Consensus forecasts do very well in the case of Germany. By contrast, during the crisis period, when GDP displayed extreme fluctuations, Consensus forecasts perform much better. At the two-quarter ahead horizon Consensus forecasts are the best model for four countries and the euro area, and at the one-quarter ahead horizon they consistently belong to the top-three models. For Spain and the Netherlands the difference is substantial. This suggests that analysts are better able to handle extreme observations of GDP growth once they have occurred, while the quality of recursively estimated models in mechanical procedures is more susceptible to extreme observations in the sample, in particular when truly forecasting. Our findings support the findings of Lundquist and Stekler (2012) who conclude that professional forecasters are responsive to information about the economy and adjust their predictions quickly. We find that despite this head start, in most cases private sector forecasts still fall behind the best model as the horizon becomes shorter and more timely monthly information is available to improve forecasts. For example, the RMSFE of backcasts by Consensus forecasts is between 20% and 84% larger than the RMSFE associated with the best model (static or dynamic factor model).

Despite the fact that Consensus forecasts are a rather poor predictor of GDP on their own, the results for the encompassing test show that they often contain valuable extra information, which may be used to improve mechanical forecasts for the euro area and all countries except Italy. The most striking results concern the backcasts by analysts, even though these actually reflect relatively dated information. Measured over the whole sample period, enriching mechanical forecasts with subjective Consensus forecasts delivers a gain in accuracy of around 10% on average. During the crisis period Consensus forecasts, unlike their statistical competitors, still offer added value for the euro area and some countries. This holds in particular for Spain and to a lesser extent for the Netherlands. During the pre-crisis period forecasts for Germany and the euro area may benefit from Consensus forecasts. The outcomes of the encompassing test suggests that subjective private sector forecasts potentially contain information that sophisticated mechanical forecasting procedures are unable to pick up.

[17] Consensus forecasts are available for the euro area from March 2002 onward only, so results in Table V refer to the period 2003.III-2011.III for the euro area.

Table V: Comparison Consensus Forecasts with best statistical model

Eval. period	1996.I-2011.III			1996.I-2007.IV			2008.I-2011.III		
Indicator	RMSFE	rank	gain	RMSFE	rank	gain	RMSFE	rank	gain
Euro area									
2Q ahead	**0.99**	1	**0.98**	1.21	13	.	**0.98**	1	**0.97**
1Q ahead	**1.06**	3	**0.98**	1.42	13	.	**1.04**	2	**0.98**
nowcast	1.34	5	**0.99**	1.43	13	**0.99**	1.34	4	.
backcast	1.77	7	**0.93**	1.54	13	**0.83**	1.84	7	**0.95**
Germany									
2Q ahead	**1.04**	7	.	**1.05**	10	**0.99**	**1.04**	7	.
1Q ahead	**1.06**	3	**0.99**	**0.99**	1	**0.95**	1.12	3	.
nowcast	1.12	3	**0.98**	**0.91**	1	**0.90**	1.35	6	.
backcast	**1.00**	2	**0.91**	**0.76**	1	**0.76**	1.40	6	**0.99**
France									
2Q ahead	**1.05**	8	**0.98**	1.23	13	.	**0.98**	1	**0.97**
1Q ahead	1.18	7	.	1.30	13	.	1.11	3	.
nowcast	1.29	8	**0.99**	1.32	13	**0.99**	1.27	4	.
backcast	1.27	6	**0.95**	1.30	11	**0.97**	1.36	6	**0.95**
Italy									
2Q ahead	1.11	13	.	1.32	13	.	**0.99**	1	**0.99**
1Q ahead	1.17	12	.	1.40	13	.	**1.01**	2	**0.97**
nowcast	1.36	11	.	1.45	13	**0.99**	1.27	4	.
backcast	1.47	12	**0.99**	1.43	13	**0.97**	1.67	6	.
Spain									
2Q ahead	**0.98**	1	**0.94**	1.23	13	.	**0.88**	1	**0.87**
1Q ahead	1.10	3	**0.96**	1.27	13	.	**0.99**	1	**0.90**
nowcast	1.21	2	**0.96**	1.36	13	.	1.13	2	**0.85**
backcast	1.10	2	**0.88**	1.27	12	.	**0.85**	1	**0.57**
Netherlands									
2Q ahead	**1.06**	9	**0.98**	1.27	13	.	**0.90**	1	**0.90**
1Q ahead	1.11	3	**0.97**	1.17	13	**0.99**	1.05	2	**0.95**
nowcast	1.23	9	**0.98**	1.29	13	**0.99**	1.15	3	**0.95**
backcast	1.39	12	**0.91**	1.56	13	**0.98**	1.20	4	**0.87**

Notes: RMSFE: RMSFE(Consensus)/RMSFE(best statistical model), entries in boldface indicate that Consensus forecasts are a competitive forecasting procedure; rank: ranking among 13 procedures (12 statistical models and Consensus forecasts); gain: RMSFE(combination of Consensus and best statistical model)/RMSFE(best statistical model), figures in boldface indicate that encompassing test is statistically significant at the 5% level.

6 Conclusion

This paper makes two contributions to the empirical literature on forecasting real GDP in the short run. The first contribution is a systematic comparison of eleven statistical linear models for five countries (Germany, France, Italy, Spain and the Netherlands) and the euro area, utilizing the same information set across countries and the euro area. Our sample period (1996.I-2011.III) allows us to compare the models' forecasting abilities in the period before the financial crisis of 2008 (Great Moderation) and the much more volatile subsequent period (financial crisis and its aftermath). The second contribution concerns the potential usefulness of (subjective) forecasts made by professional analysts. Such forecasts are very cheap and easy to use, and they may incorporate valuable information that goes beyond purely statistical data.

We summarize our findings in five points. First, monthly indicators contain valuable information that can be extracted by mechanical statistical procedures, in particular as the horizon shortens and more monthly information is processed. The largest gains in accuracy are for nowcasts and backcasts, suggesting that statistical models are especially helpful when they are able to use information that pertains to the quarter of interest. Moreover, statistical models are generally more efficient in extracting monthly information in volatile times. Their relative strength is thus to improve the assessment of the current state of the economy. By contrast, predictions by statistical models generally incorporate little information at the two-quarter ahead horizon.

Second, the dynamic and static factor models consistently display the best forecasting capabilities in the euro area and across countries in the period 1996.I-2011.III. Their relatively strong performance in the volatile crisis episode is key to this result. The dominance of factor models is somewhat weaker during the more stable period of the Great Moderation.

Third, regarding the question of which model features are critical to success, we find that employing factor analysis to summarize the available monthly information clearly delivers better results than the alternative of averaging indicator-based forecasts in the case of nowcasts and backcasts. Factor strategies work better than pooling strategies. Moreover, allowing for mixed frequencies and autoregressive terms (GDP's own past) in forecasting procedures leads to minor improvements in forecast reliability. All of these effects are more pronounced during the crisis period, implying that the cost of employing a suboptimal forecasting model is larger in periods of high volatility.

Fourth, statistical models significantly differ in the rate at which they are able to absorb monthly information as time goes by. However, the information content of the resulting forecasts appears to overlap to a large extent and the unique model-specific component appears to be small (in relation to the best model). The different models do not seem to have a comparative advantage of extracting a certain type of information, offering perspectives that complement each other. The scope for improving GDP forecasts by combining the 'views' of various models is rather limited in economic terms, although there are some exceptions. This is particularly true during volatile episodes when reliable assessments of the current situation and short run prospects are most needed, unfortunately.

Lastly, forecasts by professional analysts, which contain judgmental elements, appear to be a different category. Such forecasts are in many cases a rather poor predictor of GDP compared to the best statistical model. However, they tend to perform better during the crisis, when it really counts, and they often embody information that sophisticated mechanical forecasting procedures fail to pick up. Subjective private sector forecasts thus seems to offer the potential of enhancing mechanical forecasts.

The results of our large-scale comparative analysis may useful to policy makers, financial analysts and economic agents alike, as information on where the economy stands and where it is heading to in the short run is particularly valuable in times of great uncertainty. The dynamic factor model and the static factor model, which is a quite simple procedure from a technical point of view, are obvious candidate models for generating short term forecasts in practice.

An interesting topic for future research is to investigate how the potential of judgmental forecasts may be taken on board in mechanical statistical procedures in a real time context. Another issue that deserves an in-depth investigation is the construction of optimal weighting schemes for statistical procedures that follow the pooling strategy. Although we find that factor models in general perform better than models that pool indicator-specific forecasts, this may be due to suboptimal weighting schemes. As the latter category of models offers the attractive opportunity to calibrate weights on the basis of recent forecasting performance, the issue of optimal weights should be looked into further.

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A Appendix

A.1 Database

Table VI: Database description

nr	description	type	transform			country					
			log	dif.	filt.	EA	DE	FR	IT	ES	NL
1	World Trade (CPB)	Sales	1	1	3	‘77	‘77	‘77	‘77	‘77	‘77
2	World Industrial Production (CPB)	Sales	1	1	3	‘91	‘91	‘91	‘91	‘91	‘91
3	Ind. production United States	Sales	1	1	3	‘77	‘77	‘77	‘77	‘77	‘77
4	Ind. production United Kingdom	Sales	1	1	3	‘77	‘77	‘77	‘77	‘77	‘77
5	Ind. production (excl. construction)	Sales	1	1	3	‘77	‘77	‘77	‘77	‘77	‘77
6	Ind. production, cons. goods ind.	Sales	1	1	3	‘80	‘80	‘77	‘77	‘77	‘90
7	Ind. production, energy	Sales	1	1	3	‘80	‘80	‘77	‘80	‘80	‘90
8	Ind. production, interm. goods ind.	Sales	1	1	3	‘77	‘80	‘77	‘77	‘77	‘95
9	Ind. production, capital goods	Sales	1	1	3	‘77	‘80	‘77	‘77	‘77	‘77
10	Ind. production, manufacturing	Sales	1	1	3	‘77	‘78	‘77	‘77	‘80	‘77
11	Ind. production, construction	Sales	1	1	3	‘85	‘78	‘85	‘95	‘88	‘85
12	New orders manufacturing	Sales	1	1	3	‘95	‘91	‘00	‘90	‘00	‘95
13	New passenger cars (reg.)	Sales	1	1	3	‘90	‘90	‘90	‘90	‘90	‘90
14	New commercial vehicles (reg.)	Sales	1	1	3	‘90	‘90	‘90	‘90	‘90	‘90
15	Retail trade volume	Sales	1	1	3	‘77	‘77	‘77	‘90	‘95	‘77
16	Unemployment rate	Sales	0	1	3	‘83	‘91	‘83	‘83	‘86	‘83
17	Unemployment rate United Kingdom	Sales	0	1	3	‘83	‘83	‘83	‘83	‘83	‘83
18	Unemployment rate United States	Sales	0	1	3	‘83	‘83	‘83	‘83	‘83	‘83
19	Exports	Sales	1	1	3	‘00	‘89	‘89	‘89	‘89	‘89
20	Imports	Sales	1	1	3	‘00	‘89	‘89	‘89	‘89	‘89
21	Total HICP-index	Prices	1	2	3	‘77	‘77	‘77	‘77	‘77	‘77
22	Core HICP-index	Prices	1	2	3	‘77	‘77	‘77	‘77	‘77	‘77
23	CPI, food	Prices	1	2	3	‘90	‘77	‘77	‘77	‘93	‘77
24	CPI, energy	Prices	1	2	3	‘90	‘77	‘77	‘77	‘77	‘77
25	HICP, services	Prices	1	2	3	‘90	‘85	‘90	‘87	‘92	‘87
26	Producer prices (total, excl. constr.)	Prices	1	2	3	‘81	‘77	‘77	‘77	‘77	‘77
27	World commodity prices, total	Prices	1	2	3	‘77	‘77	‘77	‘77	‘77	‘77
28	World commodity prices, raw mat.	Prices	1	2	3	‘77	‘77	‘77	‘77	‘77	‘77
29	World commodity prices, food	Prices	1	2	3	‘77	‘77	‘77	‘77	‘77	‘77
30	World commodity prices, metals	Prices	1	2	3	‘77	‘77	‘77	‘77	‘77	‘77
31	World commodity prices, energy	Prices	1	2	3	‘77	‘77	‘77	‘77	‘77	‘77
32	Oil price (1 month future Brent)	Prices	1	2	3	‘77	‘77	‘77	‘77	‘77	‘77
33	M1	Finan.	1	1	3	‘77	‘80	‘77	‘80	‘80	‘80
34	M3	Finan.	1	1	3	‘77	‘77	‘77	‘77	‘77	‘77
35	Interest rate on mortgage	Finan.	0	1	3	‘03	‘82	‘80	‘95	‘84	‘80
36	3 month interest rate euro	Finan.	0	1	3	‘94	‘77	‘77	‘77	‘77	‘77
37	10 year government bond yield	Finan.	0	1	3	‘77	‘94	‘77	‘77	‘80	‘77
40	Headline stock-index	Finan.	1	1	3	‘77	‘77	‘77	‘77	‘87	‘77
41	Basic Material-index	Finan.	1	1	3	‘77	‘77	‘77	‘77	‘87	‘77
42	Industrials stock-index	Finan.	1	1	3	‘77	‘77	‘77	‘77	‘87	‘77
43	Consumer goods stock-index	Finan.	1	1	3	‘77	‘77	‘77	‘77	‘87	‘77
44	Consumer services stock-index	Finan.	1	1	3	‘77	‘77	‘77	‘87	‘77	‘77

Continued on next page...

Table VI – Continued

nr	description	type	transform log	dif.	filt.	country EA	DE	FR	IT	ES	NL
45	Financials stock-index	Finan.	1	1	3	‘77	‘77	‘77	‘77	‘87	‘77
46	Technology stock-index	Finan.	1	1	3	‘77	‘88	‘77	‘86	‘99	‘85
47	Loans to the private sector	Finan.	1	1	3	‘91	‘80	‘80	‘83	‘80	‘82
48	Exchange rate, US-Dollar per Euro	Finan.	1	1	3	‘80	‘80	‘80	‘80	‘80	‘80
49	Real effective exchange rate (CPI)	Finan.	1	1	3	‘77	‘77	‘77	‘77	‘77	‘77
50	Ind. conf. - headline	Survey	0	1	3	‘85	‘85	‘85	‘85	‘87	‘85
51	Ind. conf. - Order-book expect.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘87	‘85
52	Ind. conf. - Stocks expect.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘87	‘85
53	Ind. conf. - Production expect.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘87	‘85
54	Ind. conf. - Employment expect.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘87	‘85
55	Cons. conf. - headline	Survey	0	1	3	‘85	‘85	‘85	‘85	‘86	‘85
56	Cons. conf. - Financial sit.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘86	‘85
57	Cons. conf. - General ec. sit.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘86	‘85
58	Cons. conf. - Unemployment expect.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘86	‘85
59	Cons. conf. - Major purchases expect.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘86	‘85
60	Constr. conf. - Headline	Survey	0	1	3	‘85	‘85	‘85	‘85	‘89	‘85
61	Constr. conf. - Order book (evolution)	Survey	0	1	3	‘85	‘85	‘85	‘85	‘89	‘85
62	Constr. conf. - Employment expect.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘89	‘85
63	Retail conf. - Headline	Survey	0	1	3	‘85	‘85	‘85	‘85	‘88	‘86
64	Retail conf. - Current Stocks (volume)	Survey	0	1	3	‘85	‘85	‘85	‘85	‘88	‘86
65	Retail conf. - Orders expectations	Survey	0	1	3	‘85	‘85	‘85	‘85	‘88	‘86
66	Retail conf. - Business expect.	Survey	0	1	3	‘85	‘85	‘85	‘85	‘88	‘86
67	Retail conf. - Employment expect.	Survey	0	1	3	‘86	‘85	‘85	‘86	‘88	‘86
68	PMI United States	Survey	0	1	3	‘77	‘77	‘77	‘77	‘77	‘77
69	PMI United Kingdom	Survey	0	1	3	‘92	‘92	‘92	‘92	‘92	‘92
70	OECD Composite Leading ind. UK	Other	0	1	3	‘77	‘77	‘77	‘77	‘77	‘77
71	OECD Composite Leading ind. US	Other	0	1	3	‘77	‘77	‘77	‘77	‘77	‘77
72	OECD Composite Leading ind.	Other	0	1	3	‘77	‘77	‘77	‘77	‘77	‘77

Notes: type: sales=production and sales, finan.= monetary and financial, price= price data, survey= surveys; transform: log: 0=no logarithm, 1=logarithm, dif.: degree of differencing 1=first difference, 2=second difference; filt.: 3= change against the same month of the previous month.

A.2 State space representations

A.2.1 Mixed frequency VAR

This section describes the state space representation of the mixed frequency VAR described in Section 2.3.2. Let $p^* = \max(p, 3)$ and the transition equation of state vector is as follows:

$$\begin{bmatrix} z_{i,t+1} - \mu_{z_i} \\ z_{i,t} - \mu_{z_i} \\ \dots \\ z_{i,t-p^*+2} - \mu_{z_i} \end{bmatrix} = \begin{bmatrix} A_1 & A_2 & \dots & A_p & 0_{2\times 2(3-p^*)} \\ I_{2(p^*-1)} & & & & 0_{2(p^*-1)\times 2} \end{bmatrix} \begin{bmatrix} z_{i,t} - \mu_{z_i} \\ z_{i,t-1} - \mu_{z_i} \\ \dots \\ z_{i,t-p^*+1} - \mu_{z_i} \end{bmatrix} + \begin{bmatrix} \Sigma_\varepsilon^{1/2} \\ 0_{2(p^*-1)\times 2} \end{bmatrix} v_t, \tag{18}$$

where $v_t \sim N(0, I_2)$. The measurement equation is:

$$z_{i,t}^Q - \mu_{z_i^Q} = \begin{bmatrix} 1/3 & 0 & 1/3 & 0 & 1/3 & 0 & 0_{1\times(p^*-6)} \\ 0 & 1 & 0 & 0 & 0 & 0 & 0_{1\times(p^*-6)} \end{bmatrix} \begin{bmatrix} z_{i,t} - \mu_{z_i} \\ z_{i,t-1} - \mu_{z_i} \\ \dots \\ z_{i,t-p^*+1} - \mu_{z_i} \end{bmatrix} \tag{19}$$

Since, y_t^Q is only available in the third month of the quarter we substitute the missing observations in months 1 and 2 with a random draw from the standard normal distribution $N(0, 1)$, as in Mariano and Murasawa (2010). We modify the measurement equation of month 1 and month 2 in accordance with the missing observation treatment. For months for which y_t^Q is unavailable, the upper row of the matrix on the right hand side of equation 19 is set equal to zero and white noise is added.

A.2.2 Dynamic factor model

The equations of the DFM, i.e equation 3 and 5 to 7 can be cast in state space form as llustrated below for the case of $p = 1$. The aggregation rule is implemented in a recursive way in equation 21 by introducing a latent cumulator variable Ξ for which: $\Xi_t = 0$ for t corresponding to the first month of the quarter and $\Xi_t = 1$ otherwise. The monthly state space representation is given by the following observation equation:

$$\begin{bmatrix} x_t \\ y_t^Q \end{bmatrix} = \begin{bmatrix} \Lambda & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f_t \\ y_t \\ \hat{y}_t^Q \end{bmatrix} + \begin{bmatrix} \xi_t \\ \varepsilon_t^Q \end{bmatrix} \tag{20}$$

and the transition equation:

$$\begin{bmatrix} I_r & 0 & 0 \\ -\beta' & 1 & 0 \\ 0 & -\frac{1}{3} & 1 \end{bmatrix} \begin{bmatrix} f_{t+1} \\ y_{t+1} \\ \hat{y}_{t+1}^Q \end{bmatrix} = \begin{bmatrix} A_{r1} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \Xi_{t+1} \end{bmatrix} \begin{bmatrix} f_t \\ y_t \\ \hat{y}_t^Q \end{bmatrix} + \begin{bmatrix} \zeta_{t+1} \\ \varepsilon_t \\ 0 \end{bmatrix} \tag{21}$$

The application of the Kalman filter and smoother provides the minimum mean square linear estimates (MMSLE) of the state vector $\alpha_t = (f_t, y_t, \hat{y}_t^Q)$ and enables predicting quarterly GDP growth y_t^Q and dealing efficiently with an unbalanced dataset of missing observations at the beginning and at the end of the series by replacing the missing data with optimal predictions. Moreover, the two-step estimator allows for dynamics of the common factors and the cross-sectional heteroskedasticity of the idiosyncratic component.

A.3 Sensitivity analysis and additional empirical results

This section first presents a sensitivity analysis regarding the three different pooling schemes we considered (see Section 3.3). Table VII to XII report results on the RMSFE for each weighting scheme for the BEQ, QVAR, MFVAR, MIDAS, BEQ-AR and MIDAS-AR model. Next, the section presents additional results for the two subperiods, the Great Moderation and the financial crisis (see Section 4.3). Table XIII and XIV present results on the RMSFE of the statistical models, while Table XV and XVI present results on the marginal value of the models.

Table VII: Pooling schemes for **Quarterly Bridge Equation (BEQ)**: Equal weights, Recursive RMSFE sample, four-quarter moving moving RMSFE

		DE			FR			IT			ES			NL			EA		
	Month	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q
	month 1	0.90	0.90	0.89	0.52	0.52	0.52	0.74	0.74	0.74	0.60	0.59	0.58	0.70	0.70	0.70	0.62	0.62	0.62
2Q Forecast	month 2	0.90	0.90	0.89	0.52	0.52	0.51	0.73	0.73	0.74	0.59	0.58	0.58	0.69	0.69	0.69	0.62	0.61	0.61
	month 3	0.90	0.90	0.90	0.51	0.51	0.51	0.72	0.72	0.73	0.57	0.57	0.55	0.68	0.68	0.67	0.61	0.60	0.61
	month 1	0.89	0.89	0.90	0.50	0.50	0.50	0.72	0.72	0.73	0.57	0.56	0.55	0.67	0.67	0.66	0.60	0.59	0.59
1Q Forecast	month 2	0.88	0.88	0.87	0.49	0.49	0.48	0.71	0.71	0.71	0.56	0.55	0.53	0.66	0.66	0.64	0.59	0.58	0.57
	month 3	0.87	0.87	0.86	0.48	0.47	0.45	0.70	0.69	0.69	0.55	0.54	0.51	0.65	0.64	0.63	0.57	0.56	0.55
	month 1	0.85	0.85	0.85	0.46	0.46	0.44	0.68	0.68	0.67	0.55	0.53	0.49	0.64	0.63	0.61	0.55	0.54	0.53
Nowcast	month 2	0.84	0.83	0.84	0.46	0.45	0.43	0.67	0.66	0.65	0.54	0.52	0.47	0.63	0.62	0.57	0.54	0.53	0.52
	month 3	0.81	0.80	0.82	0.44	0.43	0.40	0.65	0.64	0.62	0.52	0.50	0.44	0.61	0.60	0.58	0.51	0.49	0.48
Backcast	month 1	0.80	0.79	0.78	0.43	0.42	0.40	0.64	0.63	0.62	0.52	0.49	0.43	0.61	0.60	0.58	0.50	0.48	0.46
	month 2	0.80	0.79	0.77	0.43	0.42	0.39	0.64	0.62	0.60	0.51	0.49	0.42	0.61	0.60	0.57	0.50	0.48	0.47

Notes: AV: equal weights pooling scheme, RC: Weight according to RMSFE, recursively calculated, 4Q: Weights according to RMSFE, calculated over the last four quarters. Grey cells indicate scheme with the lowest RMSFE.

Table VIII: Pooling schemes for **Quarterly Vector Autoregressive model (QVAR)**: Equal weights, Recursive RMSFE sample, four-quarter moving moving RMSFE

		DE			FR			IT			ES			NL			EA		
	Month	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q
	month 1	0.92	0.92	0.92	0.53	0.53	0.53	0.76	0.76	0.76	0.60	0.60	0.60	0.71	0.71	0.71	0.65	0.65	0.65
2Q Forecast	month 2	0.92	0.92	0.92	0.53	0.53	0.53	0.76	0.76	0.76	0.60	0.60	0.60	0.71	0.71	0.71	0.65	0.65	0.65
	month 3	0.92	0.92	0.91	0.53	0.53	0.55	0.74	0.74	0.74	0.58	0.57	0.56	0.70	0.70	0.70	0.64	0.64	0.64
	month 1	0.92	0.92	0.91	0.52	0.52	0.55	0.74	0.74	0.74	0.57	0.57	0.56	0.70	0.70	0.70	0.64	0.64	0.64
1Q Forecast	month 2	0.92	0.92	0.91	0.52	0.52	0.55	0.74	0.74	0.74	0.57	0.57	0.56	0.70	0.70	0.70	0.64	0.64	0.64
	month 3	0.91	0.91	0.92	0.48	0.48	0.49	0.73	0.73	0.73	0.50	0.50	0.49	0.69	0.69	0.69	0.62	0.62	0.62
	month 1	0.91	0.91	0.91	0.48	0.48	0.49	0.73	0.73	0.73	0.50	0.49	0.48	0.69	0.69	0.69	0.62	0.62	0.62
Nowcast	month 2	0.91	0.91	0.91	0.48	0.48	0.49	0.73	0.73	0.73	0.50	0.49	0.48	0.69	0.69	0.69	0.62	0.62	0.62
	month 3	0.87	0.87	0.88	0.42	0.42	0.41	0.63	0.63	0.62	0.48	0.46	0.44	0.60	0.60	0.60	0.50	0.50	0.49
Backcast	month 1	0.87	0.87	0.88	0.42	0.42	0.41	0.63	0.63	0.62	0.48	0.47	0.44	0.59	0.59	0.59	0.50	0.50	0.49
	month 2	0.87	0.87	0.88	0.42	0.42	0.41	0.63	0.63	0.62	0.48	0.47	0.44	0.59	0.59	0.59	0.50	0.50	0.49

Notes: AV: equal weights pooling scheme, RC: Weight according to RMSFE, recursively calculated, 4Q: Weights according to RMSFE, calculated over the last four quarters. Grey cells indicate scheme with the lowest RMSFE.

Table IX: Pooling schemes for **Mixed Frequency VAR (MFVAR)**: Equal weights, Recursive RMSFE sample, four-quarter moving moving RMSFE

		DE			FR			IT			ES			NL			EA		
	Month	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q
	month 1	0.91	0.91	0.92	0.51	0.51	0.52	0.75	0.74	0.74	0.61	0.60	0.61	0.71	0.70	0.70	0.62	0.62	0.63
2Q Forecast	month 2	0.91	0.91	0.86	0.50	0.50	0.50	0.75	0.74	0.74	0.61	0.60	0.59	0.70	0.70	0.74	0.61	0.61	0.61
	month 3	0.90	0.90	0.91	0.49	0.49	0.50	0.74	0.73	1.49	0.60	0.59	0.59	0.68	0.68	0.69	0.61	0.60	0.61
	month 1	0.89	0.89	1.00	0.49	0.49	0.49	0.73	0.72	0.74	0.59	0.58	0.62	0.68	0.68	0.71	0.60	0.60	0.60
1Q Forecast	month 2	0.88	0.88	0.89	0.48	0.48	0.49	0.71	0.71	0.71	0.59	0.58	0.64	0.68	0.67	0.69	0.59	0.58	0.59
	month 3	0.87	0.87	0.88	0.45	0.45	0.47	0.71	0.70	0.70	0.53	0.52	0.52	0.66	0.66	0.67	0.57	0.57	0.56
	month 1	0.86	0.86	0.85	0.44	0.43	0.44	0.69	0.68	0.86	0.53	0.52	0.53	0.63	0.63	0.64	0.55	0.54	0.54
Nowcast	month 2	0.86	0.84	0.86	0.43	0.42	0.42	0.67	0.67	0.66	0.53	0.51	0.52	0.63	0.62	0.64	0.54	0.54	0.56
	month 3	0.85	0.84	0.87	0.38	0.37	0.37	0.60	0.59	0.59	0.58	0.56	0.57	0.61	0.61	0.60	0.47	0.47	0.49
Backcast	month 1	0.83	0.81	0.86	0.36	0.36	0.37	0.60	0.59	0.59	0.57	0.55	0.53	0.60	0.60	0.61	0.47	0.46	0.48
	month 2	0.80	0.79	0.89	0.36	0.35	0.41	0.58	0.57	0.59	0.56	0.55	0.54	0.59	0.59	0.62	0.45	0.44	0.45

Notes: AV: equal weights pooling scheme. RC: Weight according to RMSFE. recursively calculated. 4Q: Weights according to RMSFE. calculated over the last four quarters. Grey cells indicate scheme with the lowest RMSFE.

Table X: Pooling schemes for **Mixed Data Sampling (MIDAS)**: Equal weights, Recursive RMSFE sample, four-quarter moving moving RMSFE

		DE			FR			IT			ES			NL			EA		
	Month	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q
	month 1	0.91	0.91	0.91	0.52	0.52	0.51	0.73	0.73	0.73	0.62	0.60	0.60	0.70	0.70	0.69	0.62	0.63	0.62
2Q Forecast	month 2	0.91	0.91	0.90	0.52	0.52	0.51	0.73	0.73	0.72	0.60	0.58	0.58	0.70	0.69	0.70	0.62	0.62	0.61
	month 3	0.90	0.90	0.90	0.51	0.51	0.51	0.73	0.72	0.72	0.59	0.54	0.57	0.69	0.69	0.68	0.61	0.61	0.61
	month 1	0.89	0.89	0.89	0.50	0.50	0.51	0.72	0.72	0.72	0.59	0.54	0.56	0.68	0.68	0.68	0.60	0.60	0.60
1Q Forecast	month 2	0.89	0.89	0.88	0.50	0.50	0.49	0.71	0.71	0.72	0.58	0.53	0.55	0.67	0.67	0.67	0.59	0.59	0.59
	month 3	0.87	0.87	0.88	0.48	0.48	0.48	0.70	0.69	0.69	0.56	0.51	0.52	0.66	0.66	0.66	0.57	0.57	0.56
	month 1	0.86	0.86	0.85	0.47	0.47	0.46	0.68	0.67	0.67	0.54	0.49	0.48	0.65	0.64	0.64	0.56	0.55	0.54
Nowcast	month 2	0.85	0.85	0.84	0.46	0.46	0.45	0.67	0.66	0.67	0.54	0.49	0.48	0.64	0.64	0.63	0.55	0.54	0.53
	month 3	0.82	0.82	0.81	0.44	0.43	0.42	0.65	0.64	0.65	0.51	0.46	0.44	0.62	0.62	0.60	0.51	0.50	0.50
Backcast	month 1	0.81	0.80	0.77	0.43	0.42	0.40	0.64	0.63	0.62	0.51	0.46	0.44	0.61	0.61	0.58	0.50	0.49	0.47
	month 2	0.80	0.79	0.68	0.42	0.41	0.39	0.63	0.62	0.60	0.52	0.46	0.42	0.61	0.60	0.56	0.50	0.48	0.42

Notes: AV: equal weights pooling scheme. RC: Weight according to RMSFE. recursively calculated. 4Q: Weights according to RMSFE. calculated over the last four quarters. Grey cells indicate scheme with the lowest RMSFE.

Table XI: Pooling schemes for **Quarterly Bridge Equation with AR-term (BEQ-AR)**: Equal weights, Recursive RMSFE sample, four-quarter moving moving RMSFE

		DE			FR			IT			ES			NL			EA		
	Month	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q
	month 1	0.90	0.90	0.90	0.52	0.52	0.52	0.74	0.74	0.74	0.60	0.59	0.60	0.70	0.70	0.70	0.62	0.62	0.62
2Q Forecast	month 2	0.90	0.90	0.89	0.51	0.51	0.51	0.74	0.74	0.74	0.59	0.59	0.58	0.69	0.69	0.69	0.62	0.61	0.61
	month 3	0.90	0.90	0.90	0.51	0.51	0.51	0.72	0.72	0.73	0.58	0.57	0.57	0.68	0.68	0.68	0.61	0.61	0.61
	month 1	0.89	0.89	0.90	0.50	0.50	0.50	0.72	0.72	0.72	0.58	0.57	0.55	0.67	0.67	0.66	0.60	0.60	0.59
1Q Forecast	month 2	0.88	0.88	0.87	0.49	0.49	0.48	0.71	0.71	0.72	0.57	0.56	0.54	0.66	0.66	0.64	0.59	0.58	0.57
	month 3	0.87	0.87	0.87	0.46	0.45	0.45	0.70	0.70	0.69	0.54	0.53	0.52	0.65	0.64	0.62	0.57	0.56	0.56
	month 1	0.86	0.85	0.84	0.44	0.44	0.43	0.68	0.68	0.67	0.54	0.52	0.48	0.64	0.63	0.61	0.55	0.54	0.53
Nowcast	month 2	0.84	0.84	0.82	0.43	0.43	0.41	0.67	0.67	0.65	0.54	0.52	0.47	0.63	0.62	0.58	0.54	0.53	0.52
	month 3	0.83	0.82	0.80	0.40	0.40	0.39	0.61	0.60	0.60	0.56	0.54	0.51	0.57	0.57	0.55	0.46	0.45	0.44
Backcast	month 1	0.81	0.81	0.78	0.39	0.39	0.38	0.60	0.60	0.59	0.56	0.54	0.49	0.57	0.56	0.55	0.45	0.44	0.43
	month 2	0.81	0.80	0.78	0.39	0.39	0.38	0.60	0.59	0.58	0.56	0.54	0.48	0.57	0.56	0.55	0.45	0.44	0.43

Notes: AV: equal weights pooling scheme. RC: Weight according to RMSFE. recursively calculated. 4Q: Weights according to RMSFE. calculated over the last four quarters. Grey cells indicate scheme with the lowest RMSFE.

Table XII: Pooling schemes for **Mixed Data Sampling with AR-term (MIDAS-AR)**: Equal weights, Recursive RMSFE sample, four-quarter moving moving RMSFE

		DE			FR			IT			ES			NL			EA		
	Month	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q	AV	RC	4Q
	month 1	0.95	0.95	0.95	0.52	0.52	0.52	0.74	0.74	0.73	0.62	0.60	0.60	0.70	0.70	0.70	0.62	0.63	0.62
2Q Forecast	month 2	0.94	0.94	0.95	0.51	0.51	0.51	0.74	0.73	0.74	0.61	0.59	0.59	0.70	0.70	0.70	0.62	0.62	0.62
	month 3	0.91	0.90	0.90	0.51	0.51	0.50	0.74	0.73	0.73	0.53	0.51	0.52	0.68	0.68	0.68	0.61	0.61	0.61
	month 1	0.90	0.90	0.89	0.50	0.50	0.50	0.73	0.72	0.72	0.53	0.51	0.52	0.67	0.67	0.67	0.60	0.60	0.61
1Q Forecast	month 2	0.89	0.89	0.88	0.49	0.49	0.49	0.72	0.71	0.71	0.53	0.50	0.51	0.66	0.66	0.64	0.59	0.59	0.58
	month 3	0.88	0.88	0.89	0.46	0.46	0.45	0.70	0.69	0.69	0.45	0.44	0.44	0.66	0.66	0.65	0.57	0.57	0.57
	month 1	0.86	0.86	0.84	0.44	0.44	0.43	0.68	0.67	0.67	0.43	0.43	0.41	0.64	0.64	0.64	0.55	0.54	0.53
Nowcast	month 2	0.85	0.85	0.85	0.43	0.43	0.42	0.67	0.66	0.66	0.42	0.41	0.39	0.64	0.63	0.62	0.53	0.52	0.52
	month 3	0.84	0.84	0.82	0.40	0.40	0.39	0.61	0.60	0.60	0.54	0.48	0.47	0.57	0.57	0.55	0.46	0.45	0.45
Backcast	month 1	0.82	0.82	0.79	0.40	0.39	0.38	0.60	0.60	0.60	0.55	0.48	0.48	0.57	0.57	0.54	0.45	0.44	0.42
	month 2	0.82	0.81	0.72	0.39	0.38	0.37	0.60	0.59	0.58	0.55	0.48	0.46	0.57	0.57	0.54	0.45	0.44	0.35

Notes: AV: equal weights pooling scheme. RC: Weight according to RMSFE. recursively calculated. 4Q: Weights according to RMSFE. calculated over the last four quarters. Grey cells indicate scheme with the lowest RMSFE.

Table XIII: Forecasting performance statistical models (RMSFE), 1996.I-2007.IV

Frequency	Quarterly					Mixed frequency						
Pool/Factor	Benchmark	Pooling			Factor	Factor	Pooling					
Model	AR	BEQ	BEQ-AR	QVAR	SFM	DFM	MIDAS	FA-MIDAS	MIDAS-AR	FA-MIDAS-AR	MFVAR	FA-MFVAR
RMSFE	(Absolute)	(Relative to AR-model)										
Euro area												
2Q ahead	*0.34*	**0.97**	**0.96**	**0.99**	**0.97**	1.05	**0.96**	0.96	1.00	1.01	**0.99**	1.02
1Q ahead	*0.34*	**0.92**	**0.93**	0.97	0.88	0.97	**0.92**	**0.92**	**0.96**	**0.96**	**1.00**	0.98
nowcast	*0.33*	0.92	0.90	0.96	0.82	0.97	0.94	**0.88**	0.90	0.90	1.04	0.92
backcast	*0.31*	0.97	0.94	0.96	**0.86**	**0.90**	0.97	**0.90**	0.84	**0.85**	1.05	0.93
Germany												
2Q ahead	*0.65*	**0.93**	**0.93**	**0.93**	**0.93**	**0.93**	**0.93**	**0.94**	**0.99**	**0.96**	0.92	**0.99**
1Q ahead	*0.65*	**0.93**	**0.94**	**0.92**	**0.92**	0.92	**0.93**	**0.95**	**0.94**	**0.95**	**0.95**	**0.94**
nowcast	*0.65*	**0.93**	**0.89**	**0.94**	0.89	**0.89**	**0.91**	**0.91**	**0.94**	**0.95**	**0.96**	**0.93**
backcast	*0.66*	**0.89**	0.86	**0.93**	**0.89**	**0.89**	**0.87**	**0.88**	**0.90**	**0.94**	0.98	**0.92**
France												
2Q ahead	*0.35*	**0.96**	**0.95**	0.98	0.89	**0.93**	**0.95**	**0.95**	0.98	1.01	**0.93**	1.02
1Q ahead	*0.35*	0.92	0.92	0.96	0.82	**0.88**	0.95	0.94	0.94	0.97	0.93	0.95
nowcast	*0.33*	0.88	0.89	0.95	0.86	0.76	0.91	0.92	0.92	0.92	0.87	0.93
backcast	*0.32*	0.82	0.92	0.95	0.77	0.72	0.87	0.90	0.76	0.82	0.93	0.85
Italy												
2Q ahead	*0.52*	**0.96**	**0.96**	**0.96**	**0.98**	**0.97**	0.95	**0.96**	**0.98**	**0.98**	**0.97**	**0.99**
1Q ahead	*0.51*	0.96	0.97	0.96	0.88	**0.91**	**0.94**	**0.96**	0.98	0.99	0.99	0.99
nowcast	*0.50*	0.92	0.91	0.96	0.87	0.80	0.94	0.93	**0.86**	**0.86**	0.94	0.85
backcast	*0.48*	0.93	0.91	0.93	0.84	0.80	0.94	0.92	**0.84**	**0.82**	0.95	0.80
Spain												
2Q ahead	*0.30*	1.04	**0.99**	1.05	**0.98**	0.96	1.07	1.03	1.05	1.07	1.02	1.01
1Q ahead	*0.28*	1.03	1.05	1.02	1.10	1.00	1.11	1.01	1.10	1.03	1.19	1.08
nowcast	0.27	1.09	1.15	1.10	1.19	1.08	1.13	1.06	1.18	1.25	1.35	1.20
backcast	0.28	1.04	1.24	1.11	1.20	1.05	1.05	1.15	1.09	1.20	1.51	1.24
Netherlands												
2Q ahead	*0.53*	**0.95**	**0.96**	**0.99**	1.00	**0.95**	0.94	**0.95**	**0.97**	**0.96**	**0.98**	**0.96**
1Q ahead	*0.53*	**0.93**	**0.92**	0.99	0.88	0.90	0.95	0.91	0.95	0.95	0.99	**0.95**
nowcast	*0.52*	0.94	0.93	0.98	0.83	**0.85**	0.95	0.93	**0.91**	0.93	1.02	0.93
backcast	*0.51*	0.93	0.94	0.97	0.78	**0.83**	0.91	0.90	0.92	0.93	1.04	0.99

Notes: AR: Autoregressive model, BEQ: Bridge equation, BEQ-AR: Bridge equation with AR term, QVAR: Vector autoregressive models, SFM: Static Factor Model, DFM: Dynamic factor model, FA-MIDAS: Factor augmented MIDAS, FA-MIDAS-AR: Factor augmented MIDAS with AR term, MFVAR: Mixed frequency vector autoregressive model, FA-MFVAR: Factor augmented mixed frequency vector autoregressive model, MIDAS: Mixed data sampling model, MIDAS-AR: MIDAS with AR-term.

Grey cells indicate models with the lowest RMSFE. Figures in boldface indicate models whose RMSFE is at most 10% larger than the RMSFE of the best model.

Table XIV: Forecasting performance statistical models (RMSFE), 2008.I-2011.III

Frequency	Quarterly					Mixed frequency						
Pool/Factor	Benchmark	Pooling			Factor	Factor	Pooling					
Model	AR	BEQ	BEQ-AR	QVAR	SFM	DFM	MIDAS	FA-MIDAS	MIDAS-AR	FA-MIDAS-AR	MFVAR	FA-MFVAR
RMSFE	(Absolute)	(Relative to AR-model)										
Euro area												
2Q ahead	*1.15*	**0.96**	**0.97**	1.02	0.94	**0.99**	**0.97**	**0.97**	1.00	1.01	**0.96**	1.10
1Q ahead	*1.15*	**0.90**	0.90	1.00	0.81	**0.85**	0.92	0.93	0.98	0.97	0.90	0.99
nowcast	*1.08*	0.83	0.81	0.96	0.63	0.56	0.86	0.82	0.80	0.77	0.84	0.73
backcast	*0.95*	0.84	0.76	0.91	0.50	0.37	0.77	0.66	0.67	0.64	0.80	0.53
Germany												
2Q ahead	*1.58*	**0.94**	**0.94**	**0.97**	0.92	**0.93**	**0.95**	**0.99**	**0.97**	1.02	**0.95**	1.02
1Q ahead	*1.54*	0.93	0.93	0.99	**0.84**	0.81	0.94	0.94	0.98	0.98	0.94	1.01
nowcast	*1.52*	0.88	0.88	0.98	0.68	0.59	0.88	0.89	0.78	0.78	0.90	0.78
backcast	*1.51*	0.80	0.81	0.95	0.60	0.47	0.71	0.76	0.56	0.58	0.87	0.60
France												
2Q ahead	*0.91*	**0.94**	0.95	1.00	0.96	0.91	0.94	0.94	1.00	1.01	0.94	1.15
1Q ahead	*0.87*	0.92	0.91	1.04	0.78	0.81	0.94	0.91	0.98	0.94	0.92	1.05
nowcast	*0.77*	0.92	0.85	0.99	0.67	0.65	0.95	0.85	0.88	0.79	0.86	0.87
backcast	*0.68*	0.95	0.83	0.94	0.51	0.58	0.93	0.81	0.69	0.69	0.86	0.68
Italy												
2Q ahead	*1.30*	**0.94**	**0.95**	**0.98**	0.91	**0.95**	**0.93**	**0.94**	**0.95**	**0.95**	**0.94**	1.03
1Q ahead	*1.18*	**0.98**	**0.98**	1.04	0.90	**0.95**	1.00	**0.98**	1.03	1.01	**0.98**	1.08
nowcast	*1.14*	0.91	0.91	1.01	**0.68**	0.66	0.94	0.91	0.85	0.84	0.90	0.86
backcast	*1.09*	0.88	0.84	0.91	0.47	0.53	0.87	0.84	0.66	0.65	0.83	0.68
Spain												
2Q ahead	*1.07*	0.96	1.00	0.99	**0.93**	0.87	0.98	0.97	1.00	1.00	1.02	1.04
1Q ahead	*0.94*	1.01	1.02	1.03	**0.77**	0.73	1.02	0.92	1.04	0.95	1.12	1.05
nowcast	*0.82*	0.98	1.02	0.98	0.72	0.54	0.96	0.86	0.98	0.87	1.09	1.04
backcast	*0.87*	0.79	0.90	0.82	0.55	0.43	0.82	0.88	0.78	0.95	0.90	1.04
Netherlands												
2Q ahead	*1.11*	0.97	**0.97**	1.00	1.04	1.04	**0.99**	**0.99**	1.06	1.07	**0.98**	1.19
1Q ahead	*1.10*	0.89	0.89	0.99	0.76	0.87	0.94	0.93	1.01	0.99	0.94	1.07
nowcast	*1.04*	0.79	0.78	0.96	**0.65**	0.63	0.88	0.85	0.76	0.76	0.84	0.76
backcast	*0.93*	0.87	0.78	0.89	0.63	0.57	0.88	0.79	0.71	0.68	0.89	0.71

Notes: AR: Autoregressive model, BEQ: Bridge equation, BEQ-AR: Bridge equation with AR term, QVAR: Vector autoregressive models, SFM: Static Factor Model, DFM: Dynamic factor model, FA-MIDAS: Factor augmented MIDAS, FA-MIDAS-AR: Factor augmented MIDAS with AR term, MFVAR: Mixed frequency vector autoregressive model, FA-MFVAR: Factor augmented mixed frequency vector autoregressive model, MIDAS: Mixed data sampling model, MIDAS-AR: MIDAS with AR-term.

Grey cells indicate models with the lowest RMSFE. Figures in boldface indicate models whose RMSFE is at most 10% larger than the RMSFE of the best model.

Table XV: Marginal value of statistical models, 1996.I-2007.IV

Frequency	Quarterly					Mixed frequency						
Pool/Factor	Benchmark	Pooling			Factor	Factor	Pooling					
Model	AR	BEQ	BEQ-AR	QVAR	SFM	DFM	MIDAS	FA-MIDAS	MIDAS-AR	FA-MIDAS-AR	MFVAR	FA-MFVAR
RMSFE	(RMSFE(combination of alternative and best model)/RMSFE(best model))											
Euro area												
2Q ahead	.	.	.	.	**0.99**	.	1.00	.	.	.	.	.
1Q ahead	.	1.00	.	.	.	.	.	.	.	.	.	.
nowcast	.	.		.	.	.	.	0.99	0.99	0.99	.	0.99
backcast	.	.	.	0.99	**0.97**	**0.92**	.	0.99	.	.	.	.
Germany												
2Q ahead	.	0.99	0.99	1.00	0.99	**0.99**	0.99	0.99	.	1.00	.	.
1Q ahead	0.99	**0.99**	**0.99**	**0.97**	.	.	**0.99**	**0.99**	0.99	0.99	**0.99**	**0.99**
nowcast	.	.	**0.98**	1.00	.	**0.98**	0.99	**0.99**	.	.	.	.
backcast	.	.	.	.	**0.97**	**0.97**	0.99	.	0.99	0.99	.	0.99
France												
2Q ahead	.	1.00	0.99	.	.	.	**0.99**	0.99	.	.	**0.99**	.
1Q ahead	.	.	.	.	.	.	.	0.99	.	.	0.99	.
nowcast	.	0.99	.	.	**0.99**	.	.	.	.	.	0.99	.
backcast	.	0.99	.	.	**0.97**	.	.	.	0.99	0.99	.	0.99
Italy												
2Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	0.99	.	.	0.99	0.99	0.99	.	**0.99**
backcast	.	1.00	0.99	0.99	0.99	.	0.99	0.99	**0.99**	**0.98**	.	**0.95**
Spain												
2Q ahead	**0.99**	.	**0.99**	.	**0.99**	.	.	.	.	.	**0.99**	.
1Q ahead	**0.96**	**0.99**	**0.99**	0.98	0.99	.	.	**0.97**	.	**0.99**	.	.
nowcast	.	**0.99**	.	.	**0.97**	**0.96**	0.99	0.99	**0.96**	**0.97**	.	**0.98**
backcast	.	**0.96**	.	.	**0.91**	**0.91**	**0.97**	.	**0.91**	**0.94**	.	**0.95**
Netherlands												
2Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
1Q ahead	.	.	.	.	.	.	.	1.00	.	.	.	.
nowcast	.	.	.	.	.	**0.97**	.	1.00	**0.99**	0.99	.	**0.99**
backcast	.	.	0.99	0.99	.	0.99	0.99	0.99	0.99	0.99	0.99	**0.99**

Notes: AR: Autoregressive model, BEQ: Bridge equation, BEQ-AR: Bridge equation with AR term, QVAR: Vector autoregressive model, SFM Static Factor Model, DFM: Dynamic factor model, FA-MIDAS: Factor augmented MIDAS model, FA-MIDAS-AR: Factor augmented MIDAS model with AR term, MFVAR: Mixed frequency vector autoregressive model, FA-MFVAR: Factor augmented mixed frequency vector autoregressive model, MIDAS: Mixed data sampling model, MIDAS-AR: MIDAS model with AR-term.

Grey cells indicate model with the lowest RMSFE. Figures in boldface indicate that the encompassing test is statistically significant at the 5% level.

Table XVI: Marginal value of statistical models, 2008.I-2011.III

Frequency	Quarterly					Mixed frequency						
Pool/Factor	Benchmark	Pooling			Factor	Factor	Pooling					
Model	AR	BEQ	BEQ-AR	QVAR	SFM	DFM	MIDAS	FA-MIDAS	MIDAS-AR	FA-MIDAS-AR	MFVAR	FA-MFVAR
RMSFE	(RMSFE(combination of alternative and best model)/RMSFE(best model))											
Euro area												
2Q ahead	.	0.99	1.00	.	.	.	1.00	.	.	.	0.99	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	.	.	.	.	.	.	.	.
backcast	.	.	.	.	0.99	.	0.99	0.98	.	.	.	0.96
Germany												
2Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	.	.	.	.	.	.	.	.
backcast	.	.	.	.	.	.	.	.	.	.	.	.
France												
2Q ahead	0.99	0.99	0.99	0.99	.	.	0.99	0.99	.	.	0.98	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	0.99	.	.	.	.	.	.	.
backcast	0.98	.	.	0.99	.	.	.	.	.	.	0.99	.
Italy												
2Q ahead	.	.	.	.	.	.	0.99	.	.	.	.	.
1Q ahead	0.98	0.99	0.99	0.99	.	.	0.99	0.99	.	.	0.99	.
nowcast	.	.	.	.	.	.	.	.	.	.	.	.
backcast	.	.	.	.	.	.	.	.	.	.	.	.
Spain												
2Q ahead	**0.97**	0.98	0.99	0.98	.	.	0.97	0.97	.	.	0.99	.
1Q ahead	0.98	.	.	0.99	**0.95**	.	0.99	0.98	.	.	.	.
nowcast	0.97	.	.	.	.	.	.	.	.	.	.	.
backcast	**0.90**	0.99	.	**0.93**	.	.	0.99	.	.	.	.	.
Netherlands												
2Q ahead	.	.	.	.	0.99	.	.	.	.	.	.	.
1Q ahead	.	.	.	.	.	.	.	.	.	.	.	.
nowcast	.	.	.	.	**0.94**	.	.	.	.	.	.	.
backcast	0.99	0.99	0.97	0.99	0.98	.	0.99	0.98	.	.	0.99	.

Notes: AR: Autoregressive model, BEQ: Bridge equation, BEQ-AR: Bridge equation with AR term, QVAR: Vector autoregressive model, SFM Static Factor Model, DFM: Dynamic factor model, FA-MIDAS: Factor augmented MIDAS model, FA-MIDAS-AR: Factor augmented MIDAS model with AR term, MFVAR: Mixed frequency vector autoregressive model, FA-MFVAR: Factor augmented mixed frequency vector autoregressive model, MIDAS: Mixed data sampling model, MIDAS-AR: MIDAS model with AR-term.

Grey cells indicate model with the lowest RMSFE. Figures in boldface indicate that the encompassing test is statistically significant at the 5% level.

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