A comparison of bottom-up approaches and direct forecasts of German GDP in a data-rich environment

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Abstract

The paper analyzes the performance of leading indicators for forecasting GDP in Germany. We focus on the performance of single and pooled leading indicators using various weighting schemes. Both forecasting GDP directly and the use of disaggregated procedures are compared. We employ MIDAS regressions for various levels of information by the application of different forecasting rounds. By conducting pairwise tests to the different procedures we are able to analyze their forecast ability. Further, we apply encompassing tests to investigate whether disaggregate approaches contain information not covert by the direct approach. Our results indicate that the production side contains additional useful information for short-term forecasting.

Keywords: Contemporaneous aggregation, Leading Indicators, Model combination, Forecast Evaluation, MIDAS

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1 Introduction

It is well accepted that decisions in economic policy have to be based on assessments of current and future economic conditions. For instance, changes in monetary policy should be based on most recent and future expected developments of prices and economic activity. However, policymakers typically have imperfect knowledge of the current state of the economy since many key macroeconomic variables - including industrial production (IP), gross domestic product (GDP) or inflation - are released with a substantial publication lag. This implies that forecasting in economics is not only concerned with predicting future economic developments, the current situation and the recent past have to be forecasted as well since no official statics exist for this situation. The problem of predicting the present and the very near future is often labeled as *nowcasting* (see Banbura et al., 2010) and forecasting the recent past may be called *backcasting*.

The problem of imperfect knowledge is most evident for variables collected at low frequency (e.g. quarterly data). For Germany, many key macroeconomic variables such as GDP and private consumption are only available at quarterly frequency. The first release of GDP is available six weeks after the end of the quarter. Private consumption and other GDP components are published even one week later. As a consequence, for judging the current economic condition one has to rely on additional information sources which are more timely available and / or measured more frequently. Such additional sources consist of indicators that are related to the target variable and have either leading indicator properties or are released more timely (e.g. monthly industrial production as indicator for quarterly GDP). An effective tool for forecasting,nowcasting and backcasting must use the current available information effectively to provide reliable "early estimates" of the target variable. Typically, this involves additional complications due to mixed frequency (monthly data to forecast quarterly GDP) and ragged/jagged edge data structures (according to their timeliness different variables will have missing observation at the end of the sample).

This paper concentrates on early estimates of GDP growth for the German economy. GDP is a well-accepted and comprehensive measure of economic development that covers the economy as a whole, rather than a single sector or market. We present a framework for forecasting, nowcasting and backcasting that incorporates a large set of available information of monthly and quarterly indicators from various sources including financial variables, survey indicators, composite leading indicators and real economic indicators ("hard" data such as industrial production, turnovers, new orders,...). Given different levels of available information we establish different forecasting rounds (twice a month) to simulate the forecasting process in pseudo real-time. Therefore leading indicator regression models are employed, where each individual indicator is modeled separately. Afterwards, model averaging strategies are applied to generate aggregate forecasts (AIC-weights, Bayesian weights and the mean). Similar strategies have been undertaken by Rünstler and Sédillot (2003), Angelini et al. (2008) and Drechsel and Maurin (2010) for the euro area and by Kitchen and Monaco (2003) for the US. For Germany, only Kuzin et al. (2009) take into account the flow of conjunctural information in pseudo real-time time. Thus our first contribution is to analyze systematically the role of new information and incoming data to construct "real-time" estimates of quarterly real GDP growth.

The second aim of this paper is to compare the forecasting accuracy of models forecasting aggregate

GDP directly as opposed to aggregating forecasts of GDP components. Disaggregate approaches or bottom-up approaches can be either based on the demand side (e.g. by combining private consumption, investment, exports,...) or on the production side (e.g. by combining the different sectors of gross value added, e.g. production, construction, services,...). Thus this study is related to other work that analyze contemporaneous aggregation issues. In the past decade this subject has received new attention through the comparison of the forecast accuracy of aggregating country-specific forecasts versus forecasts based on aggregated euro area wide data (see, Marcellino et al., 2003, for an example). However, the analysis of the effects of contemporaneous aggregation of subcomponents for time series data in applied empirical work has not received much attention so far.[1]

For GDP, the direct approach, namely forecasting aggregate GDP, clearly dominates in the empirical literature on leading indicators (see e.g. Stock and Watson, 2003a; Banerjee et al., 2005). Nevertheless, disaggregated approaches are also used in typical fore- and nowcasting exercises. For instance, Hahn and Skudelny (2008) pursue this line of research. Moreover, for Germany the production side approach is also preferred by many practitioners (see, Cors and Kouzine, 2003) since many monthly indicators are more closely related to subcomponents of production (mainly manufacturing output) than to aggregate GDP. Forecasting subcomponents through the demand side is often done by large-scale macroeconomic models (see, e.g. Fair and Shiller, 1990). The main contribution of this paper is to analyze rigorously the out-of-sample forecasting accuracy of the different procedures: direct vs. bottom-up approaches. As a byproduct we also receive optimal forecast (given the particular information set) for each GDP subcomponent. Additionally, with our forecasting system, we can assess the relative forecast accuracy against a univariate benchmark model for each forecast round to see for which subcomponents useful indicator variables exist. Finally, by means of forecasting encompassing tests we investigate whether bottom-up approaches for forecasting GDP contains additional information not included in the direct forecasting approach.

The remainder of the paper is structured as follows. Section 2 discusses the issue of contemporaneous aggregation and its potential advantages in forecasting GDP. In section 3 the basic framework for processing the available information set is outlined including data considerations, model specifications and model combination procedures. Section 4 presents the results and section 4 concludes.

2 Contemporaneous aggregation of GDP components

Generally, the relationship between GDP and a coincident or leading indicator can be modeled on different aggregation levels. Obviously, the simplest method is to relate GDP directly on the candidate variable or alternatively modeling subcomponents of GDP depending on the indicator and afterwards adding up all the subcomponents to an aggregate GDP forecast. Based on the methodology of national accounting (see European Communities et al., 2009; Eurostat, 2008) we can distinguish two disaggregated (or bottom-up) approaches: the expenditures view (which is the demand side concept) and the production view (which is a supply oriented decomposition of the value added by industries).

[1] An exception is Hubrich (2005), who investigates whether aggregating inflation forecasts based on HICP subindices is superior to forecasting aggregate HICP inflation directly.

2.1 Some considerations on contemporaneous aggregation

The theoretical literature on contemporaneous aggregation of disaggregated forecasts is somewhat inconclusive about the gains in terms of forecasting ability (see, e.g. Theil, 1954; Grunfeld and Griliches, 1960, for early contributions). Only under the assumption of a known data generating process (DGP) it is well established that modeling the subcomponents and then aggregating the components does lead to lower MSFE relative to modeling the aggregate directly (see, e.g. Lütkepohl, 1984). Clearly this not much helpful for empirical application where the DGP is generally unknown and where parameters have to be estimated and the models may be prone to mis-specifications and / or structural instabilities. Thus in the end, it will be an empirical question whether it is advantageous to model GDP by means of disaggregation or by modeling the aggregate.

In our setting, irrespectively whether we consider an bottom-up approach for GDP based on the production side or from the demand side, the contemporaneous aggregate can be expressed as

$$y_t^{agg} = w_{1t} y_t^1 + w_{2t} y_t^2 + ... + w_{nt} y_t^n \quad \text{for } t = 1, ...T, \tag{1}$$

where the y_t^i's are the subcomponents of y_t^{agg}, n are the number of subcomponents and the w_{it}'s are the aggregation weights. In our case, the y_t^{agg} and y_t^i's are growth rates of aggregate GDP and the i'th subcomponent, respectively. We allow the weights to be time varying due to reflect changes in the composition of aggregate GDP and we assume the weights to add up to 1, i.e. $\sum_i w_{it} = 1$.[2] We denote the direct forecast of the aggregate variable by $\hat{y}_t^{agg}$ and an indirect forecast of the aggregate variable computed by aggregating the disaggregated forecasts $\hat{y}_t^i$ $(i = 1, ..., n)$ as $\hat{y}_{sub,t}^{agg} = \sum_i w_{it} \hat{y}_t^i$.

Estimation uncertainty of the different specifications typically introduces a trade-off between potential biases due to not fully considering the heterogeneous (and disaggregated) system and increasing variance due to estimating a potentially unnecessary large number of parameters (Hendry and Hubrich, 2010). Thus the problem of disaggregation is related to the problem of model selection, where the inclusion of additional parameters also reduces the bias but increases the variance. Disaggregation also means an increase of additional parameters and thus additional uncertainty.

Related literature is concerned with the question whether it is advantageous to incorporate national information to forecast Euro area aggregates (see e.g. Marcellino et al., 2003; Cristadoro et al., 2005). A similar research question than ours is raised by Hubrich (2005) who investigates the usefulness of disaggregating the HICP into its subcomponents and than compare the outcome of the a direct approach with the disaggregate procedure. She finds that disaggregation does often not results in lower forecast errors compared to directly modeling the aggregate inflation rate. Carson et al. (2010) compare the forecasting accuracy of a direct (country wide) approach for modeling the air travel demand in the US with those of airport specific modeling. They strongly advocate a disaggregate modeling approach and find large gains by aggregating the disaggregate forecasts. Zellner and Tobias (2000) are also concerned with forecasting GDP growth rates, but at an international level. They find the disaggregation of

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[2] Note that we do not restrict the weights to be strictly positive, since the growth contribution of inventories might be also negative.

international forecasts on a country level basis improves forecast accuracy, but only when also aggregate information is used for the specification within countries.

From a practical perspective we would expect that a disaggregate approach for forecasting is advantageous whenever there exist a potentially large number of indicators that are directly related to specific subcomponents of expenditure variables or branches, but only weakly connected with the aggregate as a whole. Thus heterogeneity in the subcomponents may translate into inaccurate predictions of the direct approach. Fair and Shiller (1990) compare direct and bottom-up approaches for forecasting GDP in the US. They find that disaggregation improves forecasting accuracy. Their study compares a structural macroeconometric model with a simple production-side approach and pure time-series models for aggregate GDP. Thus they do not take into account the full conjunctural information at each forecasting point.

2.2 Practical implementation of aggregation

Gross Domestic Product (GDP) is the value of goods and services produced by a particular country and there are various ways to decompose the national product into parts, such that the sum of the components equals the national product. The two most popular decompositions include the production side approach and the demand side approach.[3] Although the dominant method to fore- and nowcast GDP is the direct approach where aggregate growth rates are regressed on one or more leading indicators also disaggregated approaches exist. Cors and Kouzine (2003) for Germany, Barhoumi et al. (2008) for France and Hahn and Skudelny (2008) for the Euro area also follow a production side approach but do not consider a comparison to direct or demand side approaches. Demand side leading forecasts are made by Parigi and Schlitzer (1995) for Italy, Baffigi et al. (2004) for the euro area and Golinelli and Parigi (2007) for the G7 countries.

The expenditure approach

The expenditure approach makes use of the fact that production equals domestic expenditures made on final goods and services. Thus the standard demand identity holds:

$$Y = C + CG + IC + INC + INV + X - M,$$

which consists of private consumption (C), government consumption (CG), construction investment (IC), remaining gross fixed investment (INC), inventories (INV) and exports (X) minus imports (M). Note that we disaggregated gross fixed investment into two separate components. The first component is construction investment which includes both residential and non-residential building investments. The second component is gross fixed investment. All quantities are measured as real, chain-linked quantities which are seasonally and calendar adjusted.[4]

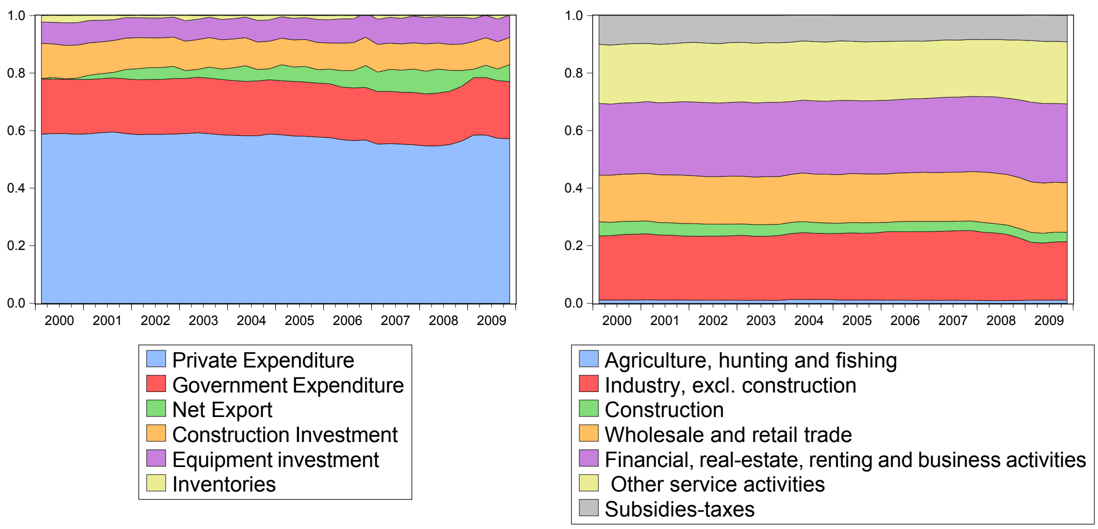
[3] Additionally, production equals income and can thus be decomposed into different kinds of income.

[4] Due to the fact that inventories are not separately released by the Federal Statistical Office we compute this series by subtracting all the remaining components from GDP.

By far the largest subcomponent on the expenditure side is private consumption which constitutes about 58% of GDP in 2009 (see Figure 1). Government consumption and gross fixed investment are with respective shares of 20% and 18% the second and third important categories, although much smaller than private consumption. Since Germany runs a trade surplus the last years, the trade surplus is positive and around 5% in real terms.

Figure 1: Share of GDP

(a) Expenditure Approach **(b) Output Approach**



Source: German Statistical Office, author's calculation.

The corresponding GDP growth forecast from the expenditure side is the weighted average of the forecasts of demand components which is $\hat{y}^{agg}_{demand,t} = \sum_i w_{it}\hat{y}^i_t$. The weights are computed as a moving average of most recent contribution (last 4 quarters) to GDP which equals $w_{it} = 1/4\sum_{j=1}^{4}\frac{Z_{i,t-j}}{Y_{t-j}}$ for each subcomponent Z_i. This allows us to consider the time-varying composition of the expenditure shares due to both business cycle fluctuations and long-term developments.

The production side approach

The supply side approach measures the value of output produced by each industry using the concept of value added. To arrive at GDP one has to consider indirect taxes minus subsidies which can be expressed as:

$$Y = Y^{PS} + Y^{CO} + Y^{TT} + Y^{FB} + Y^{PP} + Y^{AF} + \text{TAXES} - \text{SUBSIDIES},$$

where the individual sectors constitute of production (excluding construction) (PS), construction (CO), wholesale and retail trade, hotels and restaurants and transport (TT), financial, real estate, renting and business services (FB), public and private services (PP) as well as agriculture, hunting and fishing (AF). The sectors follow the classification by the NACE classification (Nomenclature générale des activités économiques dans les Communautés Européennes). This classification scheme is applied in the European Union since 1970 and is revised in 2002 (NACE, rev.1.1). Again the analysis relies on quarterly seasonal and calendar adjusted real quantities.

The largest share in production is captured by the service sector. Financial, real estate, renting and business services and public and other services account for approximately 27% and 21% of total production, respectively. Followed by the production sector (excl. construction) with 21% which is relatively high for an industialized country. The wholesale and retail trade, hotels and restaurants and transport sector represents 17%. Whereas the sectors of construction (3%) and agriculture (1%) are of minor importance within the production components. Further, the remaining component for GDP (taxes minus subsidies) has a growth share of 9%. As with the demand components, each supply component is forecasted separately and then all components are aggregated to a joint GDP forecast. Weights for the individual sectors are again computed based on their most resent GDP share.

3 Framework for processing the available information

When it comes to forecasting GDP - either by its components or directly - we have to take into account several important issues. First, a preferably large and informative data set on leading indicators have to be considered. Then econometric models have to be specified that take into account indicators (possibly) sampled at different frequencies. Since we estimate many different models using only one individual indicator per model, we employ forecast combination techniques to summarize all the relevant information from the models and indicators.

3.1 Data set

Our dataset contains 273 indicators in monthly or quarterly frequency (see Table 5 in the appendix). According to their nature the series can be grouped into 7 blocks — (i) *financial data*, (ii) *real economic indicators*, (iii) *prices*, (iv) *survey measures*, (v) *international indicators*, (vi) *composite indicators* and (vii) *government variables*. Financial data (49) includes interest rates, interest spreads, stock prices, stock price volatilities, monetary aggregates and exchange rates. Real economic variables comprise 94 series of industrial production (for the aggregate as well as for industry branches and good categories), turnovers (both for the domestic and foreign markets and for different categories), wholesale trade, export and imports, new orders (for different industries, including orders from abroad), car registrations and labor market variables (employment, unemployment, wages, vacancies as well as hours worked). Price data (14) contain consumer prices, producer prices, export and import prices, commodity prices and wholesale prices. As to survey data, we use 79 series constituting of consumer and producer surveys from the ifo (core indices as well as subcomponents for different industries, capacity utilization and world climate), ZEW, European Commission, Markit (PMI) and GfK. International indicators include sentiment indicators from major trading partners (US, France, UK), industrial production in the US, key financial variables (Dow Jones, US bond yields) and composite indicators for other industrialized countries (US, China, Asia, Italy). Composite leading indicators for Germany (4) are employed from the OECD and the Commerzbank (Early Bird). Finally, we use government revenue data (6) consisting of income and turnover taxes as well as customs duties.

All indicators are made stationary by transformation – either differences or log-differences are used (ADF tests are conducted for all series, and in cases where non-stationarity cannot be rejected, data transformations are applied to ensure stationarity of the variables).[5]

An important issue for simulating realistic forecasting settings is to take intoaccount the publication lags of relevant leading indicators. Typically, data sets contain missing observations at the end of the in-sample period; this is known as the ragged-edge problem. Depending on the specific forecasting data, the available data set will continuously vary due to manifold lags in publication of the respective indicators. For the applied researcher, it is desirable to be able to get an estimate for current-quarter GDP growth that can be updated instantaneously as new data (new information) on the set of indicators becomes available. To reflect the different states of information, we consider several forecast rounds over the whole quarter until the GDP flash is published (45 days after the end of the reference quarter). Therefore, 9 forecasts are generated at bi-monthly frequency using all the available information.

Table 1: Forecast Design

month of publication lag forecast round		0	0.5	1	1.5	2	2.5	3
1	M1 Beginning	M12	M11	M11	M10	M10		
2	M1 Middle	M12	M12	M11	M11	M10	M10	
3	M2 Beginning	M1	M12	M12	M11	M11	M10	M10
4	M2 Middle	M1	M1	M12	M12	M11	M11	M10
5	M3 Beginning	M2	M1	M1	M12	M12	M11	M11
6	M3 Middle	M2	M2	M1	M1	M12	M12	M11
7	M4 Beginning	M3	M2	M2	M1	M1	M12	M12
8	M4 Middle	M3	M3	M2	M2	M1	M1	M12
9	M5 Beginning	M4	M3	M3	M2	M2	M1	M1

Note: For each forecast round (1-9), the given information state is shown. M1 to M12 indicate the monthly information for January to December.

Table 1 shows the structure of our pseudo real-time forecasting exercise as an illustration. Starting with the first forecast, i.e. at the beginning of the first month of a quarter (e.g. January 1st), our data set includes monthly indicators that are early available in time (e.g. financial variables can be directly used from December) or with substantial lags (e.g. building permits are published with a delay of about 2 months). Over the forecast rounds, more and more recent information becomes available and can be also considered for estimation.

3.2 Single Model specifications

A further complication of the analysis lies in the fact that many leading indicators are available at monthly frequency whereas the target variable, GDP growth, is only available at quarterly frequency. Therefore, the traditional way when facing this complication is to transform the higher frequent variable to match the frequency of the target variable (usually one takes as conversion method the mean or the last value). One practical approach that has been considered in the literature is the bridge equation approach where GDP growth is regressed on a quarterly-converted monthly indicator (see Kitchen and

5 Results are available upon request.

Monaco, 2003; Rünstler and Sédillot, 2003). However, the optimal conversion method is generally unknown and may vary from one forecasting round to the next.[6] Therefore Angelini et al. (2008), Schumacher and Breitung (2008), Aruoba and Diebold (2010) and Banbura et al. (2010) employ a state-space approach to solve the data misalignment. Usually, the lower-frequency (target) variable is modeled and forecasted at a higher frequency with factors that reflect the current state of information.

We apply MIxed Data Sampling (henceforth MIDAS) regression models to circumvent the problems of quarterly conversion (this approach has been proposed by Ghysels et al., 2004, 2007; Andreou et al., 2011) and successfully applied by Clements and Galvão (2009) and Marcellino and Schumacher (2010) to macroeconomic forecasting. MIDAS models are closely related to distributed lag models (see Judge et al., 1985) and use parsimonious polynomials to reflect the dynamic response of a target variable to change is the explanatory variables. The parsimonious specification is particularly useful for time series that do not change much from one month to another (which may imply that explanatory variables are nearly linearly dependent). Thus one does not need to estimate an unrestricted model using all observed monthly data points which would result in an highly parameterized dynamic model. The main advantage is that for the distributed lag specification only a small number of parameters needs to be estimated although long lags can be captured.

The standard MIDAS model with a single explanatory variable is given by

$$y_t = \beta_0 + B(L^{1/m};\theta)x^m_{t-h} + \epsilon^m_t \tag{2}$$

where $B(L^{1/m};\theta) = \sum_{k=1}^{K} b(k;\theta)L^{(k-1)/m}$ and $L^{s/m}x^m_{t-1} = x^m_{t-1-s/m}$. t indexed the time unit of interest (in our case, quarters), m is the higher sampling frequency (i.e. $m = 3$ for monthly data) and K is the maximum number of lags. We parameterize $b(k;\theta)$ as an Almon Distributed Lag model which can be represented as:

$$b(k;\theta) = \theta_0 + \theta_1 k + \theta_2 k^2 + ... + \theta_q k^q, \tag{3}$$

where q is the polynomial degree ($q < K$) which can be substantially lower than K. Even with very small q many flexible forms can be approximated.[7] Estimation is done by restricted least squares. In many applications for q a relative small number is sufficient to allow for a flexible adjustment. In practice one has to make a choice for q and K. We use information criteria, namely the AIC, to evaluate different combinations of q and K for the in-sample period and choose the one with the lowest value.

In the MIDAS specification eq. 2 the target variable y_t is directly related to information available at $t - h$. h does therefore reflect the exact state of monthly information ($h = 0, 1/3, 2/3, 3/3, ...$). This

[6] As far as monthly industrial production data is concerned which has a direct relationship to gross value added in the production sector as well as to GDP, one cannot expect that the most recent value is always the important value compared to those in the past.

[7] Note that by applying the standard Almon Lag model, we deviate from the existing literature, since most applications utilize the Exponential Almon Lag model where the weights are always positive. This restriction is sometimes needed, e.g. for GARCH models where negative weights are undesirable (see Ghysels et al., 2007). In this application we do not need this restriction which then allows us to choose a linear estimation strategy (restricted least squares) instead of a non-linear procedure.

implies that given different information assumptions for the current quarter $b(k;\theta)$ can generally vary for different forecasting rounds and depending on the publication lag h is specified. Under the assumption that one month of the actual quarter is already available and $K = 12$ (one year of information) and $m = 3$ (three observation within one quarter) the MIDAS regression model equals

$$y_t = \beta_0 + B(L^{1/3};\theta)x^3_{t-2/3} + \epsilon^3_t, \tag{4}$$

so that

$$y_t = \beta_0 + b(0;\theta)x^3_{t-2/3} + b(1;\theta)x^3_{t-1} + b(2;\theta)x^3_{t-1-1/3} + ... + b(K;\theta)x^3_{t-4-1/3} + \epsilon^3_t. \tag{5}$$

According to Clements and Galvão (2009) one may also include autoregressive dynamics into the model. We also consider this model which can be expressed as

$$y_t = \lambda y_{t-1} + \beta_0 + B(L^{1/3};\theta)\left(1 - \lambda L^1\right)x^3_{t-h} + \epsilon^3_t. \tag{6}$$

Whether the standard or autoregressive augmented version is used is decided according the AIC.

While the MIDAS approach is employed for the indicators available at monthly frequency, for the remaining quarterly variables we take a standard ARDL approach following Stock and Watson (2003a):

$$y_t = \alpha + \sum_{i=l}^{p} \beta_i y_{t-i} + \sum_{j=k}^{q} \gamma_j x_{t-j} + u_t, \tag{7}$$

where u_t is an error term and α, β and γ are regression coefficients to be estimated. l and k reflecting potential publication lags of the indicators as well as of the dependent variable. As with MIDAS the respective lag length p and q is selected by AIC.

3.3 Model combination

While some single indicator models may provide sufficient forecast accuracy, it may be undesirable to rely on such a limited set of information. As discussed above, we employ a large set of coincident and leading indicators and thus throwing away the majority information by employing one single best (in-sample) fitting model is in most situations inefficient. One way to employ the full set of available information is to pool the results of several models. The combination of forecasts often results in an improvement of forecast accuracy compared to a univariate benchmark models or to a single modeling strategy (see Granger and Newbold, 1977; Stock and Watson, 2004; Timmermann, 2006). An additional advantage of model averaging is that it guards against instabilities (Hendry and Clements, 2004) and often results in a more stable and reliable forecasting performance (see Drechsel and Scheufele, 2010, before and during the financial crisis).

Pooling the individual indicator forecasts $\widehat{Y}_{i,t}$ we obtain the total forecast $\tilde{Y}^h_{t,t+h}$ by:

$$\tilde{Y}_t = \sum_{i=1}^{n} \omega_{i,t} \widehat{Y}_{i,t} \quad \text{with} \quad \sum_{i=1}^{n} \omega_{i,t} = 1 \tag{8}$$

where $\omega_{i,t}$ being the weight assigned to each indicator forecast that results from the i^{th} individual equation. Note that due to the subscript t we allow for time-varying weights. Model averaging can be both employed for the direct GDP forecasts as well as for the individual GDP components either by the supply or by the demand side. To arrive at the final combined forecast given the individual forecasts from the various models one has not to specify the exact model weight.

Combination according to in-sample information

Since in our regression setting the individual forecasts are exclusively model based, one can employ equation specific information to construct these weights. As proposed by Bates and Granger (1969) and further extended to multiple forecasts by Granger and Newbold (1977) the optimal combination scheme for one-step ahead unbiased forecasts can be calculated based on the variance covariance structure of forecast errors. Granger and Ramanathan (1984) show that the lowest mean-square error can be obtained by regressing the realization on the individual forecasts – the weights are then estimated based on a restricted least square estimate (where it is assumed that the weights sum up to one). Given the estimated models one can use the residuals (and the in-sample fit) of the individual models to calculate these weights (this approach follows Granger and Ramanathan and is referred to as GR thereafter). This requires solving the quadratic minimization problem:

$$Q = (y - F\omega)^{'}(y - F\omega), \tag{9}$$

subject to the convexity constraint $0 \leq \omega \leq 1$ and the additivity constraint $\sum_{i=1}^{n} \omega_i = 1$. F is the matrix of the models in-sample predictions and y is the target variable to be forecasted. The weights are obtained by $\hat{\omega} =$ argmin $Q(\omega)$ subject to the specified constraints. From a theoretical point of view, this should lead to optimal combination weights. However, in practice, this approach often suffers from overparameterization when the number of predictors is high in relation to the sample size.

To circumvent somehow the estimation uncertainty of the covariance approach of Granger and Ramanathan, Diebold and Pauly (1990) suggest shrinking towards equal weights. The equal weighting scheme is very simple and have been shown to provide reasonable good results. Therefore a Bayesian shrinkage estimator can be used with the prior $\omega \sim N(\mu, \sigma^2_\omega I)$ where σ^2_ω is a scalar and I is an identity matrix. Then the shrinkage estimator is given by

$$\hat{\omega} = (F^{'}F + \gamma I)^{-1}(F^{'}y + \gamma\mu), \tag{10}$$

while μ is a vector where each element is $\mu_i = 1/n$ and the parameter γ controls the amount of shrinkage towards the equal weights prior. The resulting estimator is thus a weighted average of an OLS estimator (GR weights) and an equal weighting scheme. Following Diebold and Pauly (1990) by employing empirical Bayes methods the shrinkage parameter is estimated as:

$$\hat{\gamma} = \hat{\sigma}^2 / \hat{\sigma}^2_{\omega}, \tag{11}$$

where

$$\hat{\sigma}^2 = \frac{1}{T} y^{'} \left[I - F(F^{'}F)^{-1}F^{'} \right] y, \quad \text{and} \quad \hat{\sigma}^2_{\omega} = \frac{y^{'}y - T\hat{\omega}^2}{trace(F^{'}F)}.$$

$\hat{\sigma}^2$ is the mean square error under OLS weights and $\hat{\sigma}^2_{\omega}$ is the ratio of the fitted regression variance and the average variance of the forecasts. The shrinkage parameter γ gets large when the variance of the forecasts is large or when the R^2 given the OLS weights is small. Computationally the shrinked weights are obtained by minimizing

$$Q = \frac{(y - F\omega)^{'}(y - F\omega)}{\hat{\sigma}^2} + \frac{(\omega - \mu)^{'}(\omega - \mu)}{\hat{\sigma}^2_{\omega}}, \tag{12}$$

subject to the positivity constraints.

As a third model averaging scheme employing the full in-sample covariance information, we consider Mallows Model Averaging (MMA) criterion proposed by Hansen (2007) and Hansen (2008). This measure is based on Mallows (1973) criterion for model selection. The goal of this measure is to minimize the MSE over a set of feasible forecast combinations. This done by minimizing the function

$$C = (y - F\omega)^{'}(y - F\omega) + \omega^{'}Ks^2, \tag{13}$$

where K is a vector including the number of coefficients of each model and $s^2 = (T - k(M))^{-1}\hat{e}(M)^{'}\hat{e}(M)$ is an estimate σ^2 from the model with the smallest estimated error variance. Again we employ the constraints $0 \leq \omega \leq 1$ and $\sum_{i=1}^{n} \omega_i = 1$. In contrast to the first two combination schemes, MMA explicitly takes into account the number of estimated parameters of the model.

Another related procedure which is even simpler and does not take into account the complete covariance structure is based on information criteria. This approach has been proposed by Burnham and Anderson (2004) and successfully applied to macroeconomic forecasting by Kapetanios et al. (2008); Drechsel and Maurin (2010). Intuitively the model with the lowest AIC receive the highest weight. More specifically the weights are calculated as

$$\omega_i^{AIC} = \frac{\exp\left(-0.5 \cdot \Delta_i^{AIC}\right)}{\sum_{i=1}^{n} \exp\left(-0.5 \cdot \Delta_i^{AIC}\right)} \quad \text{with} \quad \Delta_i^{AIC} = AIC_i - AIC_{\min}, \tag{14}$$

this procedure is sometimes also referred to as smoothed AIC weights.[8]

Another way of combining models in a Bayesian framework for forecasting purpose is proposed by Wright (2008, 2009). Weights are constructed in proportion to the posterior probability of each model, which can be calculated as

$$\omega_i \propto (1+\phi)^{-p_i/2} S_i^{-T}, \tag{15}$$

where $S_i^2 = Y'Y - Y'\hat{Y}_i \frac{\phi}{1+\phi}$. $\hat{Y}_i$ is the vector of model i's in sample predictions, p_i denotes the number of parameters in model i and T is the number of in-sample observations. Parameter ϕ controls the degree of shrinkage. The smaller ϕ is, the stronger the degree of shrinkage (which makes the prior more informative). If ϕ is large, one moves away from the model prior in response to what the data say.[9] As noted by Wright (2008) it is not clear what the optimal degree of shrinkage is for the purpose of obtaining good forecasts. Like Kapetanios et al. (2008), we also consider three variants in the degree of shrinkage: $\phi = 0.5$ (high shrinkage), $\phi = 2$ (medium shrinkage) and $\phi = 20$ (low shrinkage).

All combination methods discussed so far are employed in each estimation stage (and thus optimized at each forecast step) which implies that weights, the ω's, are allowed to vary over time. Due to the rolling estimation scheme employed for our models this may partly guard against instabilities over time. As an additional modeling scheme and as an additional benchmark we take the model including the best in-sample performance which we measure by the model minimizing the AIC (which we refer to as minAIC).

Combination according to the out-of-sample performance

Forecast combination weights can be also obtained by referring to previous out-of-sample forecast errors. These weights are most appropriate in cases of structural instabilities. We purposely construct the out-of-sample weights in the same quasi-real-time setting in which we construct our forecasts. This implies that we can use the information in past forecast errors only when they can be observed (so we consider a relevant information lag). For instance, we observe GDP only with some time lag and when the new forecast is made only some past forecasts error are known. We can therefore only include forecast errors until $t-h$. It also implies that, for the first few runs, when there is no out-of-sample information available, we use the equal weighting scheme until the first past forecasts can be compared with their corresponding realization.

As shown by Stock and Watson (2003b, 2004) and Drechsel and Scheufele (2010) high forecasting accuracy can be obtained by employing weights based on discounted mean square forecast errors (MSFEs). This means that current weights are inversely proportional to the forecast errors of the recent past. This

8 A similar approach is based on the R^2 where the weights are computed as $\omega_i^{R^2} = \exp\left(-0.5 \cdot \Delta_i^{R^2}\right) / \sum_{i=1}^{n} \exp\left(-0.5 \cdot \Delta_i^{R^2}\right)$ with $\Delta_i^{R^2} = R^2_{\max} - R^2_i$.

9 Note that the Wright (2008) weighting scheme (assuming low shrinkage) is related to information theoretic weighting schemes. Both take into account the in-sample model fit and penalize the model complexity (i.e. the number of estimated parameters).

obviously implies that the most recent best indicators obtain a relatively high weight. This approach follows that of Bates and Granger (1969), who successfully applied similar techniques.

Discount mean square forecast error weights are based on

$$w_{i,t} = \frac{\lambda_{it}^{-1}}{\sum_{j=1}^{n} \lambda_{jt}^{-1}} \tag{16}$$

where $\lambda_{it} = \sum_{s=T_0}^{t-h} \delta^{t-h-s} \left(\hat{e}_{i,s}^{h}\right)^2$ with δ being the discount factor and $\hat{e}_{i,s}^{h}$ the forecast error of model i. Note that imposing $\delta = 1$ (no discounting) implies long memory, meaning that all estimation errors in the sample are equally important. The other extreme is $\delta = 0$, where only the most recent best performance is considered. The literature tends to set δ between 0.9 and 1 (see Stock and Watson, 2004).

3.4 Forecast Evaluation

To analyze the forecast performance of our different models and to evaluate whether a disaggregated forecasting approach is preferable to the direct one we run an simulated out-of-sample forecast comparison. Therefore, we specify a first in-sample period from 1992q1-2003q4 and then compute forecasts for 2004q1 (given 9 different states of available information). Next, we roll the sample by one observation (1992q2-2004q1) and calculate another 9 forecasts for 2004q2. This procedure is repeated until 2010q3 where the last forecasts are obtained. The employed procedure employs recursive forecasts by adopting a rolling window where the in-sample estimation period is fixed.

Given the obtained forecasts we examine the forecast errors for the specified out-of-sample period. We concentrate on the mean squared forecast error (MSFE) as a benchmark loss function. More precisely, we compute root mean squared forecast errors (RMSFE) for different pooling techniques and a benchmark model (simple univariate time series model). The latter is a forecast from a univariate autoregressive model which corresponds to forecasts from eq(7), where no further indicator x is specified.

We denote $\widehat{Y}_{i,t}^{j}$ as the forecast with indicator or model combination i obtained either by the direct, the supply side or the demand side approach (j=direct, supply or demand) and $\widehat{Y}_{0,t}^{j}$ as the benchmark forecast obtained by a direct or bottom-up approach. The forecast error is then defined as the realizations Y_t minus the forecasts which gives the corresponding forecast errors $\widehat{e}_{i,t}^{j} = Y_t - \widehat{Y}_{i,t}^{j}$. One obvious way to evaluate the forecast accuracy of a candidate model or a forecast combination procedure is to calculate relative RMSFEs (relative to the benchmark) given by

$$relative\ RMSFE = \frac{\sqrt{\sum_{t=T_1}^{T_2} \left(Y_t^j - \widehat{Y}_{i,t}^{j}\right)^2}}{\sqrt{\sum_{t=T_1}^{T_2} \left(Y_t^j - \widehat{Y}_{0,t}^{j}\right)^2}} = \frac{\sqrt{\sum_{t=T_1}^{T_2} \left(\widehat{e}_{i,t}^{j}\right)^2}}{\sqrt{\sum_{t=T_1}^{T_2} \left(\widehat{e}_{0,t}^{j}\right)^2}}, \tag{17}$$

where T_1 indicates the first date of the pseudo out-of-sample forecast and T_2 is the last date where the last forecast is observed. Whenever the average performance of the indicator forecast is better than the AR forecast, the relative RMSFE is smaller than one.

However, the RMSFE (or relative RMSFE) measure provides no evidence whether the difference is statistically significant. A more formal test procedure to decide which models to be preferred is necessary. By appling a rolling forecast comparison experiment, we can use the Giacomini and White (2006) test of unconditional predictive ability to conduct pairwise tests of equal predictive ability. This implies that one can ignore the consequences of parameter uncertainty even when models are nested (see West, 1996). This test also enables the comparison of forecast combination schemes.

Besides deciding whether one model performs significantly better than an alternative (on average). We also ask whether there is additional information contained in alternative approaches by means of encompassing. Therefore we perform encompassing tests in the augmented version of Harvey et al. (1998). Specifically, we test whether the supply and/or the demand side approach contains any information beyond that already contained in the direct approach. Thus the test regression is specified as follows:

$$\widehat{e}_{i,t}^{direct} = \lambda_1 \left(\widehat{e}_{i,t}^{direct} - \widehat{e}_{i,t}^{supply}\right) + \lambda_2 \left(\widehat{e}_{i,t}^{direct} - \widehat{e}_{i,t}^{demand}\right) + v_t \tag{18}$$

for each modeling scheme i. The corresponding null hypothesis equals

$$H_0: \ \lambda_1 = \lambda_2 = 0,$$

whenever this null hypothesis cannot be rejected this indicates that the direct approach encompasses the bottom-up approaches. This would imply that there is no additional information contained in the disaggregate approaches.

4 Forecasting Results

This section summarizes the results for forecasts of GDP growth obtained by various weighting schemes for direct and disaggregated forecasting approaches. Forecasts for GDP growth are made in 9 different forecasting steps (bi-monthly) until the first GDP estimate of the statistical office is released. We also report the results for the individual GDP components using various model averaging schemes. Next we compare the direct approach with the production and expenditure approach based on the respective forecasting accuracy.

4.1 Forecasts obtained with the direct approach

Table 3 shows the forecasting results based on the direct approach by using different combination schemes. As expected the average forecast errors decrease for most pooling techniques as more and more information can be employed. For the first forecast rounds (F1-3) we do not find any combination scheme

Table 2: GDP forecast comparison

	F1	F2	F3	F4	F5	F6	F7	F8	F9
AR	1.202	1.202	1.202	1.198	1.198	1.198	1.198	1.198	1.198
AIC	0.996	0.972	0.952	0.994	0.970	0.965	0.919**	0.896**	0.879**
R2	0.993	0.971	0.951	0.995	0.972	0.969	0.924**	0.902**	0.885**
Wright20	1.430	1.332	1.135	1.047	1.107	0.955	0.942	0.847	0.861
Wright2	1.449	1.363	1.100	1.068	1.097	1.043	1.013	0.977	1.010
Wright0.5	1.083	1.063	1.028	1.058	1.058	1.039	1.029	0.997	0.995
mean	0.995	0.972	0.951	0.995	0.972	0.968	0.923**	0.901**	0.883**
min AIC	1.564	1.166	1.537	1.530	1.428	1.416	1.452	1.461	1.431
gr	1.177	1.109	1.145	1.128	1.136	1.033	0.984	0.873*	1.064
shrink	1.133	1.065	1.032	1.021	1.005	0.947	0.899*	0.863**	0.909*
MMA	1.202	1.174	1.167	0.877*	0.814*	1.026	0.952	0.770*	0.748**

Note: Relative RMSFE for direct GDP forecasts based on various weighting schemes are shown for the 9 forecast rounds (compared to the AR forecast given in the first line).

that significantly outperforms the benchmark univariate time series model. Thus, leading indicator forecasts based on the direct approach does not turn out to be useful within the first six weeks within the quarter, After this period some combination schemes provide useful information (in particular MMA at stage 4 and 5). The last forecasting rounds turn out to be very informative and the average RMSFE can be reduced quite substantially (by about 20% or more) within the last 3 forecasting rounds.

4.2 Forecasting the aggregates

If one turns to the disaggregate approaches, it is evident that some components can be forecasted very well, while for other variables there is no information within the coincident and leading indicators (see Tables 6 and 7). Also for the components the general picture is that the forecasting accuracy improves over the forecast rounds. For the production approach we find that the producing sector (excl. construction) can be reproduced very well. This is not surprising since many of the indicators are more or less connected with this sector. Improvements of leading indicator forecasts for this sector are substantial and highly significant. For the sectors financing, renting and corporate services, wholesale, retail trade and transport and construction some signals from leading indicators are sent and some model averaging schemes turn out to be better than the benchmark model. For the remaining sectors no reliable information is provided. The situation for the demand side is similar. Exports, imports, building and equipment investment are the aggregates that can be forecasted using the information of leading indicators. For private consumption which has by far the largest expenditure share, no model averaging scheme turns out to be helpful. Also for government consumption and inventories the benchmark model cannot be outperformed.

4.3 Comparing the direct forecast with disaggregate approaches

Table 3 shows pairwise comparisons of the three different forecasting procedures for different combination schemes and for all forecasting rounds. It turns out that at the first forecasting round (the beginning of the quarter) for pooled methods both demand and supply side methods display smaller forecasting errors compared to the direct approach. However no significant differences can be found

Table 3: GDP forecast comparison

	F1		F2		F3		F4		F5		F6		F7		F8		F9	
	direct	demand	direct	demand	direct	demand	direct	demand	direct	demand	direct	demand	direct	demand	direct	demand	direct	demand
AIC																		
demand	0.890		0.916		0.924		1.119*		1.099		1.090		1.089		1.120		1.109	
GVA	0.997	1.003	0.993	1.007	0.987	1.013	0.915*	1.093*	0.914*	1.095*	0.917	1.090	0.916	1.091	0.922	1.084	0.927	1.079
R2																		
demand	0.895		0.922		0.929		1.122*		1.104		1.094		1.094		1.124		1.116	
GVA	0.999	1.001	0.997	1.003	0.993	1.007	0.914*	1.094*	0.913*	1.096*	0.916*	1.092*	0.915	1.093	0.920	1.087	0.925	1.082
Wright20																		
demand	0.685		0.931		1.044		1.166		1.270		2.131*		2.011		1.563		1.620	
GVA	0.714	1.401	0.679	1.473	0.822	1.217	0.945	1.058	0.951	1.051	0.978	1.023	0.954	1.048	1.047	0.955	1.022	0.979
Wright2																		
demand	0.641		0.862		1.146		1.158		1.286*		1.760		1.943		1.329		1.369	
GVA	0.698	1.432	0.709*	1.411*	0.902	1.109	0.902	1.109	0.932	1.073	1.004	0.996	0.944	1.059	0.927	1.078	0.889	1.125
Wright0.5																		
demand	0.816		1.033		1.030		1.133		1.178		1.265		1.260*		1.064		0.990	
GVA	0.978	1.023	0.976	1.025	1.031	0.970	0.869*	1.151*	0.946	1.057	0.971	1.030	0.892	1.121	0.856*	1.169*	0.880*	1.137*
mean																		
demand	0.891		0.918		0.926		1.120*		1.101		1.092		1.091		1.122		1.112	
GVA	0.998	1.002	0.995	1.005	0.990	1.010	0.915*	1.093*	0.913*	1.095*	0.916*	1.091*	0.915	1.093	0.921	1.086	0.925	1.081
min AIC																		
demand	0.984		1.240		1.084		1.026		1.111		1.097		0.854		0.745		0.929	
GVA	0.726	1.378	0.758*	1.319*	0.688	1.454	0.640	1.562	0.650	1.539	0.573	1.745	0.574	1.743	0.564	1.773	0.558	1.794
gr																		
demand	0.994		1.020		0.991		1.241**		1.271**		1.548**		1.443*		1.499		1.207	
GVA	0.914	1.094	0.849*	1.178*	0.826*	1.210*	0.866	1.155	0.839	1.192	0.809*	1.236*	0.862	1.160	0.966	1.036	0.798**	1.254**
shrink																		
demand	0.900		0.898		0.938		1.187*		1.174		1.238		1.207		1.297		1.278	
GVA	0.925	1.081	0.888*	1.126*	0.892*	1.121*	0.917*	1.091*	0.909**	1.101**	0.881**	1.135**	0.907*	1.103*	0.905	1.105	0.877*	1.140*
MMA																		
demand	1.200*		1.239		1.458		1.942*		2.009		1.358**		1.274**		1.726		1.863	
GVA	0.908	1.101	0.824	1.213	0.811	1.233	1.072	0.933	1.176	0.850	0.866	1.155	0.948	1.055	0.956	1.046	1.019	0.982
median																		
demand	1.038		1.189		1.076		1.488**		1.600*		1.296*		1.261***		1.284**		0.869	
GVA	0.881	1.135	0.909*	1.100*	1.021	0.980	0.927	1.078	1.031	0.970	1.074	0.931	1.071	0.934	1.111	0.900	0.898	1.114

Note: For each forecast round (F1-F9) the forecasts based on the demand-side (demand) and production-side (GVA) approach are compared with the direct forecast. Further, the production-side (GVA) is compared with the demand-side forecast for all weighting schemes applied.

(the only exception is for MMA). For the second round onwards one can observe some significant improvements by employing the disaggregated production based approach (see Figure 4). Up to the last forecasting round (F9) this seems to be a robust finding. Whereas the performance of the expenditure approach is quite heterogeneous. For the first forecasting rounds the results are satisfactory, but later the forecasting performance deteriorates and the demand side approach is often found to be significantly inferior compared to the direct or bottom-up approach.

Table 4: Encompassing

	F1	F2	F3	F4	F5	F6	F7	F8	F9
AIC	***	*	**	**	**	**	**	**	**
R2	***	*	*	**	**	**	**	**	**
Wright20	***	***	***	***	***	**	*		**
Wright2	***	***	***	***	**	***	***	**	***
Wright0.5	***	***		***	***	**	***	***	***
mean	***	*	**	**	**	**	**	**	**
min AIC	***	***	***	***	***	***	***	***	***
gr	***	***	***	*	***	***	*	***	***
shrink	***	***	***	**	***	***	***	***	**
MMA	**	***	***			***	**	***	*
median	***	**			*				***

Note: XXX.

The results of the encompassing tests reveal that there is still information contained in the disaggregated approaches beyond that in the direct approach (see Table 4). This is not much surprising since in most of the times the production side approach is significantly better than the direct approach and thus employing the production side approach may offer improvements in short-term forecasting and nowcasting GDP. The success of the disaggregated approach may be attributed mainly to the fact that coincident and leading indicators are sector specific and show a strong connection in particular to the production sector but also partly to construction and wholesale trade.

5 Conclusion

This paper compares direct versus bottom-up approaches for forecasting and nowcasting GDP growth in Germany. We employ MIDAS models to bridge the gap between monthly indicators to quarterly GDP. Additionally, we make extensive use of model averaging schemes to summarize the available state of information. Our preliminary results reveal that the frequently used direct approach for forecasting GDP in Germany is not always the most efficient procedure. In particular, the information from the production side should be used to further improve the forecasting accuracy.

References

Andreou, E., Ghysels, E. and Kourtellos, A. (2011), "Forecasting with mixed-frequency data". In M. Clemens and D. Hendry (editors), "Oxford Handbook of Economic Forecasting", chap. 8., Oxford University Press.

Angelini, E., Camba-Mendez, G., Giannone, D. et al. (2008), "Short-Term Forecasts of Euro Area GDP Growth". CEPR Discussion Papers 6746, C.E.P.R. Discussion Papers.

Aruoba, S. B. and Diebold, F. X. (2010), "Real-Time Macroeconomic Monitoring: Real Activity, Inflation, and Interactions." *American Economic Review*, **100**(2), 20–24.

Baffigi, A., Golinelli, R. and Parigi, G. (2004), "Bridge models to forecast the euro area GDP". *International Journal of Forecasting*, **20**(3), 447–460.

Banbura, M., Giannone, D. and Reichlin, L. (2010), "Nowcasting". CEPR Discussion Papers 7883, C.E.P.R. Discussion Papers.

Banerjee, A., Marcellino, M. and Masten, I. (2005), "Leading Indicators for Euro-Area Inflation and GDP Growth". *Oxford Bulletin of Economics and Statistics*, **67**, 785 – 813.

Barhoumi, K., Brunhes-Lesage, V., Darné, O. et al. (2008), "Monthly forecasting of French GDP: A revised version of the OPTIM model". Documents de Travail 222, Banque de France.

Bates, J. M. and Granger, C. W. J. (1969), "The Combination of Forecasts". *Operations Research Quarterly*, **20**(4), 451–468.

Burnham, K. P. and Anderson, D. R. (2004), "Multimodel Inference – Understanding AIC and BIC in Model Selection". *Sociological Methods & Research*, **33**(2), 261–304.

Carson, R. T., Cenesizoglu, T. and Parker, R. (2010), "Forecasting (Aggregate) Demand for U.S. Commercial Air Travel". manuscript, University of California.

Clements, M. and Galvão, A. (2009), "Forecasting US output growth using Leading Indicators: An appraisal using MIDAS models". *Journal of Applied Econometrics*, **24**(7), 1187–1206.

Cors, A. and Kouzine, V. (2003), "An approach for timely estimations of the German GDP". *Allgemeines Statistisches Archiv*, **87**, 201–220.

Cristadoro, R., Forni, M., Reichlin, L. et al. (2005), "A Core Inflation Indicator for the Euro Area". *Journal of Money, Credit and Banking*, **37**(3), 539–60.

Diebold, F. X. and Pauly, P. (1990), "The use of prior information in forecast combination". *International Journal of Forecasting*, **6**(4), 503–508.

Drechsel, K. and Maurin, L. (2010), "Flow on conjunctural information and forecast of euro area economic activity". *Journal of Forecasting*, forthcoming.

Drechsel, K. and Scheufele, R. (2010), "Should We Trust in Leading Indicators? Evidence from the Recent Recession". Discussion Paper No 10, Halle Institute for Economic Research.

European Communities, O. f. E. C.-o., International Monetary Fund, Development, U. N. and Bank, W. (2009), "System of National Accounts 2008".

Eurostat (2008), "Metadata: Statistical Classification of Economic Activities in the European Community, Rev. 1.1 (2002)". `http://ec.europa.eu/eurostat/ramon`, last checked: July 2010.

Fair, R. C. and Shiller, R. J. (1990), "Comparing Information in Forecasts from Econometric Models". *American Economic Review*, **80**(3), 375–89.

Ghysels, E., Santa-Clara, P. and Valkanov, R. (2004), "The MIDAS touch: Mixed DAta Sampling regression models". mimeo, Chapel Hill, N.C.

Ghysels, E., Sinko, A. and Valkanov, R. (2007), "MIDAS Regressions: Further Results and New Directions". *Econometric Reviews*, **26**(1), 53 – 90.

Giacomini, R. and White, H. (2006), "Tests of Conditional Predictive Ability". *Econometrica*, **74**(6), 1545–1578.

Golinelli, R. and Parigi, G. (2007), "The use of monthly indicators to forecast quarterly GDP in the short run: an application to the G7 countries". *Journal of Forecasting*, **26**(2), 77–94.

Granger, C. W. and Newbold, P. (1977), *Forecasting Economic Time Series*, , . Academic Press.

Granger, C. W. and Ramanathan, R. (1984), "Improved Methods of Combining Forecasting". *Journal of Forecasting*, **3**, 197–204.

Grunfeld, Y. and Griliches, Z. (1960), "Is aggregation necessarily bad?" *The Review of Economics and Statistics*, **42**(1), 1–13.

Hahn, E. and Skudelny, F. (2008), "Early estimates of euro area real GDP growth - a bottom up approach from the production side". Working Paper Series 975, European Central Bank.

Hansen, B. E. (2007), "Least Squares Model Averaging". *Econometrica*, **75**(4), 1175–1189.

Hansen, B. E. (2008), "Least-squares forecast averaging". *Journal of Econometrics*, **146**(2), 342–350.

Harvey, D. I., Leybourne, S. J. and Newbold, P. (1998), "Tests for Forecast Encompassing". *Journal of Business and Economic Statistics*, **16**, 254–259.

Hendry, D. F. and Clements, M. P. (2004), "Pooling of forecasts". *Econometrics Journal*, **7**(1), 1–31.

Hendry, D. F. and Hubrich, K. (2010), "Combining disaggregate forecasts or combining disaggregate information to forecast an aggregate". Working Paper Series 1155, European Central Bank.

Hubrich, K. (2005), "Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy?" *International Journal of Forecasting*, **21**(1), 119–136.

Judge, G. G., Griffiths, W. E., Hill, R. C. et al. (1985), *The Theory and Practice of Econometrics*, , . John Wiley and Sons.

Kapetanios, G., Labhard, V. and Price, S. (2008), "Forecasting Using Bayesian and Information-Theoretic Model Averaging: An Application to U.K. Inflation". *Journal of Business & Economic Statistics*, **26**(1), 33–41.

Kitchen, J. and Monaco, R. (2003), "Real-Time Forecasting in Practise: The U.S. Treasury Staff's Real-Time GDP Forecast System". *Business Economics*, **38**, 10–19.

Kuzin, V., Marcellino, M. and Schumacher, C. (2009), "Pooling versus model selection for nowcasting with many predictors: An application to German GDP". Discussion Papers 7197, C.E.P.R.

Lütkepohl, H. (1984), "Forecasting contemporanously aggregated vector ARMA processess". *Journal of Business and Economic Statistics*, **2**(3), 201–214.

Mallows, C. L. (1973), "Some Comments on CP". *Technometrics*, **15**(1), 661–675.

Marcellino, M. and Schumacher, C. (2010), "Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP". *Oxford Bulletin of Economics and Statistics*, **72**(4), 518–550.

Marcellino, M., Stock, J. H. and Watson, M. W. (2003), "Macroeconomic forecasting in the euro area: Country specific versus area-wide infromation". *European Economic Review*, **47**, 1–18.

Parigi, G. and Schlitzer, G. (1995), "Quarterly forecasts of the italian business cycle by means of monthly economic indicators". *Journal of Forecasting*, **14**, 117–141.

Rünstler, G. and Sédillot, F. (2003), "Short-term estimates of euro area real GDP by means of monthly data". Working Paper Series 276, European Central Bank.

Schumacher, C. and Breitung, J. (2008), "Real-time forecasting of German GDP based on a large factor model with monthly and quarterly data". *International Journal of Forecasting*, **24**(3), 386–398.

Stock, J. H. and Watson, M. W. (2003a), "Forecasting Output and Inflation: The Role of Asset Prices". *Journal of Economic Literature*, **47**(3), 788–829.

Stock, J. H. and Watson, M. W. (2003b), "How did leading indicator forecasts perform during the 2001 recession?" *Federal Reserve Bank of Richmond, Economic Quarterly*, **89**(3), 71–90.

Stock, J. H. and Watson, M. W. (2004), "Combination forecasts of output growth in a seven-country data set". *Journal of Forecasting*, **23**(6), 405–430.

Theil, H. (1954), *Linear Aggrgation of Economic Relations*, , . North Holland.

Timmermann, A. (2006), *Forecast Combinations*, *Handbook of Economic Forecasting*, vol. 1, chap. 4, 135–196. Elsevier.

West, K. D. (1996), "Inference about Predictive Ability". *Econometrica*, **64**(5), 1067–1084.

Wright, J. H. (2008), "Bayesian Model Averaging and exchange rate forecasts". *Journal of Econometrics*, **146**(2), 329–341.

Wright, J. H. (2009), "Forecasting US inflation by Bayesian model averaging". *Journal of Forecasting*, **28**(2), 131–144.

Zellner, A. and Tobias, J. (2000), "A note on aggregation, disaggregation and forecasting performance". *Journal of Forecasting*, **19**, 457–469.

Table 5: Set of Indicators

Label	Name	Months of Publication Lags	Frequency
GDP	GDP		q
CNPER	consumer expenditure		q
EXNGS	exports of goods & services		q
IMNGS	imports of goods & services		q
EAGCTCE	Gross fixed capital formation		q
CNGOV	government consumption		q
GCCON	construction investment		q
IAUS	ausrstungsinvestitionen		q
IVOR	vorratsvernderungen, rest		q
GVAAFFD	gva - agriculture, forestry & fishing		q
GVACOND	gva - construction		q
GVAFIND	gva - financing,renting & corporate services		q
GVAINDD	gva - producing sector excl. construction		q
PAVMSCD	gva - value added - manufacturing sector		q
GVAOTHD	gva - public & private service suppliers		q
GVATRAD	gva - wholesale & retail trade & transport		q
GVATOTD	gva - total		q
GVADIFF	diff - gva -bip		q
Finance			
PQ3197A	lending to enterprises & self employed: housing loans	4.5	q
PQ3013A	mortgage loans	4.5	q
PQ3001A	lending to enterprises & self employed	4.5	q
PQ3020A	lending to manufacturing industry	4.5	q
PQ3022A	lending to construction industry	4.5	q
PQ3023A	lending to wholesale & retail trade & repair industry	4.5	q
PQ3185A	lending to service sector: housing enterprises	4.5	q
PQ3189A	lending to service sector: holding companies	4.5	q
PQA350A	bank lending to dom.enterprises & individuals: all banks	4.5	q
PQ3151A	housing loans - dom.entps.		
	hh, total, all banks	4.5	q
SU0101R	day-to-day-money market rate-frankfurt (mthly avg.)	0	m
SU0107R	three-mth money market rate - mthly avg.	0	m
PRATE	discount rate / short term euro repo rate	0	m
GBOND	long term government bond yield - 9-10 years	0	m
WU0004R	yields on fully taxed bonds outstanding - public bonds	0	m
WU0022R	yields on fully taxed bonds outstanding- corporate bonds	0	m
WU9552R	yields on lsted fedrl bnds outstndg.maturity 3-5 yrs avg. rate	0	m
WU9553R	yields on lsted fedrl bnds outstndg.maturity 5-8 yrs avg. rate	0	m
spr-10y-m	term spread (10y - policy inst)	0	m
spr-10y-d	term spread (10y - 1day)	0	m
spr-10y-3m	term spread (10y - 3m)	0	m
spr-1d-m	1day - policy inst	0	m
spr-c-g	corporate bond-government bond	0	m
SPR-NF2AE	spread corp AA- government bond	0	m
SPR-NF3BE	spread corp BBB- government bond	0	m
SPR-P3BE	spread corp financial BBB-government bond	0	m
SPR-EUCU	spread high yield -government bond	0	m
YUDM01F	german prc.competit.agst.23 selected indl.countr,cpi-basis	1	m
SHRPRCF	DAX share price index	0	m
BDINECE	nominal effective exchange rate	0	m
VDAXNEW	VDAX-new volatility index - price index	0	m
VDAXIDX	VDAX volatility index (old) - price index	0	m
MLNF2AE	corporate non-financial aa (euro)	0	m
MLNF3BE	non-financial bbb	0	m
MLNP3BE	financial bbb (euro)	0	m
MLHEUCU	high yield (euro)	0	m
TSD304B	overnight deposits - m1	1	m
M2C	money supply - m2	1	m
M3C	money supply - m3	1	m
EMECBM1	em money supply: m1 (ep)	1	m
EMECBM1FB	em money supply: m1 (flows)	1	m
EMEBM2	em money supply: m2-m1 (index)	1	m
EMEBM2F1B	em money supply: m2-m1 (flows)	1	m
EMEBM3	em money supply: m3-m2 (ep)	1	m
EMEBM3F2B	em money supply: m3-m2 (flows)	1	m
OU0123A	bank lending to domestic non-banks - short term	1.5	m
OU0175A	bank lending to entprs.& individuals - short-term	1.5	m
OU5668A	time deposits of domestic enterprises	1.5	m
OU0243A	saving deposits of domestic enterprises	1.5	m
Real Economic Indicators			
HOURSPP	hours worked: per employed person (dom.concept)	5	q
IPTOT	ip including construction	1.5	m
IPMAN	industrial production: manufacturing	1.5	m
USNA05G	ip - manufacturing: capital goods	1.5	m
USNA06G	ip - manufacturing: consumer durables	1.5	m
USNA07G	ip - manufacturing: consumer non-durables	1.5	m
USNI63G	ip - manufacturing, mining & quarrying	1.5	m
USNA25G	ip - manufacturing: chemicals & products	1.5	m

To be continued. . .

Label	Name	Months of Publication Lags	Frequency
USNA33G	ip - manufacturing: basic metals	1.5	m
USNA39G	ip - manufacturing: machinery & equipment	1.5	m
USNA50G	ip -manufacturing: motor vehicles, trailers	1.5	m
USNA61G	ip - construction	1.5	m
USNI61G	ip - energy	1.5	m
IPINT	ip - intermediate goods	1.5	m
IPCON	ip - consumer goods	1.5	m
IPEGS	ip - electricity,gas,steam & air conditioning supply	1.5	m
IPVEM	ip - motor vehicles, trailers and semi-trailers	1.5	m
STDMMQG	ind.t/o: mfg., mining & quar., dom.	1.5	m
STFMMQG	ind.t/o: mfg., mining & quar., fgn.	1.5	m
STDINTG	ind.t/o: intermediate goods, dom.	1.5	m
STFINTG	ind.t/o: intermediate goods, fgn.	1.5	m
STDCAPG	ind.t/o: capital goods, dom.	1.5	m
STFCAPG	ind.t/o: capital goods, fgn.	1.5	m
STDDURG	ind.t/o: durable cons. goods, dom.	1.5	m
STFDURG	ind.t/o: durable cons. goods, fgn.	1.5	m
STDNDUG	ind.t/o: non-durable cons. goods, dom.	1.5	m
STFNDUG	ind.t/o: non-durable cons. goods, fgn.	1.5	m
STDCONG	ind.t/o: consumer goods, dom.	1.5	m
STFCONG	ind.t/o: consumer goods, fgn.	1.5	m
STDEXEG	ind.t/o: energy exc.elec., gas, steam&hot water supply, dom.	1.5	m
STFEXEG	ind.t/o: energy exc.elec., gas, steam&hot water supply, fgn.	1.5	m
STDMANG	ind.t/o: manufacturing, dom.	1.5	m
STFMANG	ind.t/o: manufacturing, fgn.	1.5	m
STDVEMG	ind.t/o: motor veh., trailers&semi-trail., dom.	1.5	m
STFVEMG	ind.t/o: motor veh., trailers&semi-trail., fgn.	1.5	m
STDCEOG	ind.t/o: computer, electronic & optical products, dom.	1.5	m
STFCEOG	ind.t/o: computer, electronic & optical products, fgn.	1.5	m
STDCHNG	ind.t/o: chemicals & chemical products, dom.	1.5	m
STFCHNG	ind.t/o: chemicals & chemical products, fgn.	1.5	m
STDMYEG	ind. t/o: machinery & equip. n.e.c., dom.	1.5	m
STFMYEG	ind. t/o: machinery & equip. n.e.c., fgn.	1.5	m
WTEXMOG	wholesale trade excluding motor vehicles	1.5	m
WHTCFWH	wholesale trade - clothing & footwear	1.5	m
WHTCHEH	wholesale trade - chemical products	1.5	m
WHTCNMH	wholesale trade - construction machinery	1.5	m
WHTSLGH	wholesale trade - solid, liquid & gaseoUS fuels & related prods	1.5	m
XSC500D	exports (volume on basis2005)	1.5	m
XSC501D	imports (volume on basis2005)	1.5	m
NEWORDG	manufacturing orders	1.5	m
USC001G	new orders to manufacturing	1.5	m
BPRORDG	new orders to manufacturing - intermediate goods	1.5	m
CAPORDG	new orders to manufacturing - capital goods	1.5	m
CONORDG	new orders to manufacturing - consumer goods	1.5	m
DOMORDG	new orders to manufacturing - domestic	1.5	m
DBPORDG	new orders to manufacturing - domestic: intermediate goods	1.5	m
DCPORDG	new orders to manufacturing - domestic: capital goods	1.5	m
DCNORDG	new orders to manufacturing - domestic: consumer goods	1.5	m
OVRORDG	new orders to manufacturing - from abroad	1.5	m
OBPORDG	new orders to manufacturing - from abroad: intermediate goods	1.5	m
OCPORDG	new orders to manufacturing - from abroad: capital goods	1.5	m
OCNORDG	new orders to manufacturing - from abroad: consumer goods	1.5	m
USC509G	mfg orders: machinery & equipment nec, dom.	1.5	m
USC510G	mfg orders: machinery & equipment nec, fgn.	1.5	m
USC659G	mfg orders: motor vehicles, trailers, semi-trailers, dom.	1.5	m
USC660G	mfg orders: motor vehicles, trailers, semi-trailers, fgn.	1.5	m
USC587G	mfg orders: computer, elecc.&opt.prds., elecl. equip., dom.	1.5	m
USC588G	mfg orders: computer, elecc.&opt.prds., elecl. equip., fgn	1.5	m
USC203G	mfg orders: chem.&chem.prds., basic pharm.prds.&prepar., dom.	1.5	m
USC204G	mfg orders: chem.&chem.prds., basic pharm.prds.&prepar., fgn	1.5	m
USDA16G	construction orders received	1.5	m
USMB28B	turnover in construction- total	1.5	m
USMB01B	employment in construction	1.5	m
HOUSINP	housing permits issued for bldg.cnstr.: bldg.s-resl, new voln	1.5	m
NRSBLDB	construction permits granted-non-residential	2	m
USLA01B	building permits granted: all buildings	2	m
USLA02B	building permits granted: new homes and renovations	2	m
USLA05B	building permits granted: non residential-indl. cnstr.	2	m
WGUS01LAB	wg wg bldg.permits granted: all bldg.	2	m
HOURCON	hours worked	2	m
RVN	new registrations - all vehicles voln	0.5	m
RVNCARP	new registrations - cars voln	0.5	m
RVNTRUP	new registrations - heavy trucks voln	0	m
RETTOTG	retail sales excl. Cars	1	m
UNTOTQ	unemployment: % civilian labour	0	m
EMPTOTO	employed persons (residence concept,ILO)	1	m
USBA14O	employed persons (work-place concept)	1	m
EMPOWHH	employment - wholesale	1	m

To be continued. . .

Label	Name	Months of Publication Lags	Frequency
WDAYS	working days	0	m
HRWAGEF	wage & salary level on an hourly basis: overall economy	1.5	m
WAGES	wage & salary,overall economy	1.5	m
WAGMANF	wage & salary: on hrly. basis - prdg. Sector	1.5	m
MWAGINF	wage&salary level,mthly basis - prdg.sect.	1.5	m
ESEITHT	hours worked: industry (excluding construction)	1.5	m
VACTOTO	vacancies	0	m
Prices and Wages			
CONPRCE	cpi	0	m
USFB76E	cpi (excluding energy)	0.5	m
HWWAINF	Hwwa index	0.5	m
IUW510F	Hwwa index, Energy	0.5	m
IUW501F	Hwwa index, excl. Energy	0.5	m
EMEBPOILA	oil prices (euros per barrel)	0	m
UKOILBREN	UK avg. brent oil price	0	m
SAERFRLI	London gold price - US $	0	m
USZI01E	import price index	1	m
USZJ01E	export price index	1	m
WH75	wholesale output price index rebased to 1975=100	0.5	m
PRODPRE	ppi	0.5	m
Survey Indicators			
WDIFCLIMR	Economic climate - world	1.5	q
WDIFEXPER	Economic expectations - world	1.5	q
IFDMT	mfg.: capacity utilisation	1.5	q
ZEWST	ZEW present economic situation	0	m
ZEWECSR	ZEW indicator of economic sentiment	0	m
CNFBUSQ	ifo business climate index (pan germany)	0	m
IFOEXPQ	business expectations	0	m
IFOBUSQ	assessment of business situation	0	m
IFOMTLQ	business climate index: manufacturing	0	m
IFOMTKQ	business expectations: manufacturing	0	m
IFOMTAQ	assessment of business situation: manufacturing	0	m
IFDMTJQ	mfg.: exports expected next 3 mth	0	m
IFDMTMQ	mfg.: foreign orders on hand	0	m
IFDMTCQ	mfg.: inventory of finished goods	0	m
IFDMTFQ	mfg.: orders on hand	0	m
IFOMCAQ	assessment of business situation: mfg. - consumer goods	0	m
IFOMCLQ	business climate index: manufacturing - consumer goods	0	m
IFOMCKQ	business expectations: manufacturing - consumer goods	0	m
IFDMPAQ	mfg. capital goods: business sit.	0	m
IFDMIAQ	mfg. intermediate goods:business sit.	0	m
IFDMDAQ	mfg. cons. durb.: business situation	0	m
IFDMDLQ	mfg. consumer durb.: business climate	0	m
IFDMDHQ	mfg. cons. durb.: production expctd. next 3 mth	0	m
IFDMNLQ	mfg. consumer non-durb.:business climate	0	m
IFDMNAQ	mfg. cons. non-durb.: business sit.	0	m
IFDMNHQ	mfg. cons. non-durb.: prod. expctd. next 3 mth	0	m
IFDMPLQ	mfg. capital goods: business climate	0	m
IFDMPHQ	mfg. capital goods: prod. expctd. next 3 mth	0	m
IFDMILQ	mfg. intermediate goods: business climate	0	m
IFDMIHQ	mfg. interm. goods: prod. expctd. next 3 mth	0	m
IFOBDOQ	assessment of business situation: construction	0	m
IFOBDQQ	business climate index: construction	0	m
IFOBDPQ	business expectations: construction	0	m
IFDCTIQ	cnstr.ind.: assessment of orders on hand	0	m
IFPCTWQ	cnstr.ind.: unfavourableweather situation - yes	0	m
IFOWHHQ	business expectations: wholesale trade	0	m
IFOWHIQ	business climate index: wholesale trade	0	m
IFOWHAQ	assessment of business situation: wholesale trade	0	m
IFWSACQ	wholesaling: assessment of inventories	0	m
IFWSAHQ	wholesaling: expect.withregard to order activity in next 3 m	0	m
IFORTIQ	business climate index: retail trade	0	m
IFORTHQ	business expectations: retail trade	0	m
IFRSACQ	ret.sale - assessment ofinventories	0	m
IFRSAHQ	ret.sale-expect.with regard to order activity in next 3 mth	0	m
GFKECOQ	GFK consumer climate survey- business cycle expectations	0	m
GFKREVQ	GFK consumer climate survey - income expectations	0	m
GFKBUYQ	GFK consumer climate survey - willingness to buy	0	m
GFKPRFQ	GFK consumer survey: prices next 12 mths	0	m
GFKUNFQ	GFK consumer survey: unemplmt. next 12 mths	0	m
GFKFNLQ	GFK consumer survey: financial situation last 12mth	0	m
GFKFNFQ	GFK consumer survey: financial situation next 12mth	0	m
GFKECLQ	GFK consumer survey: economic situation last 12 mth	0	m
GFKECFQ	GFK consumer survey: economic situation next 12 mth	0	m
GFKPRLQ	GFK consumer survey: prices last 12 mths	0	m
GFKMPCQ	GFK consumer survey: major purchases at present	0	m
GFKMPFQ	GFK consumer survey: major purchases over next 12 mth	0	m
GFKSACQ	GFK consumer survey: savings at present	0	m
GFKSAFQ	GFK consumer survey: savings over next 12 mths	0	m

To be continued...

Label	Name	Months of Publication Lags	Frequency
CONSNT	consumers confidence index	0	m
CONSND	consumer confidence climate	0	m
CNFCONQ	consumer confidence indicator	0	m
EUSCUNQ	consumer survey: unemployment next 12 mths	0	m
EUSCFHQ	consumer survey: statement on fin.situation of household	0	m
EUSIPRQ	ind.svy: prodn.trends in recent mth	0	m
EUSIOBQ	ind.svy: order book position	0	m
EUSIEBQ	ind.svy: exp.ord.book pstn	0	m
EUSIFPQ	ind.svy: stocks of finishedgoods	0	m
EUSIPAQ	ind.svy: prod.expectation for mth.ahead	0	m
EUSISPQ	ind.svy: sell.prc.expect.mth.ahead	0	m
EUSIEMQ	ind.svy: emp.expect.for mth.ahead	0	m
EUSICIQ	industrial confidence indicator	0	m
EUSVCIQ	services confidence indicator	0	m
EUSCCIQ	consumer confidence indicator	0	m
EUSRCIQ	retail confidence indicator	0	m
EUSBCIQ	cnstr.confidence indicator	0	m
EUSESIG	economic sentiment indicator	0	m
PMIBD	PMI manufacturing	0	m
PMIBDS	PMI services	0	m
PMIEUR	PMI composite euroland	0	m
International Indicators			
BGCNFBUSQ	Belgium business indicator survey - economy	0	m
BG000183Q	Belgium bnb bus. svy.- manufacturing - not smoothed	0	m
USUMCONEH	US univ of michigan consumer sentiment - expectations	0	m
USNAPMPR	US ism production	0	m
FREUSESIG	France economic sentiment indicator	0	m
ESEUSESIG	Spain economic sentiment indicator	0	m
POEUSESIG	Poland economic sentiment indicator	0	m
CZEUSESIG	Czech Rep. economic sentiment indicator	0	m
ITEUSESIG	Italy economic sentiment indicator	0	m
UKEUSESIG	UK economic sentiment indicator	0	m
EMDJES50	em Dow Jones Eurostoxx index	0	m
DJINDUS	Dow Jones industrials - price index	0	m
USSP500	US standard & poor's 500 stock price index	0	m
UKI61	UK govt bond yield - long term	0	m
USI61	US govt bond yield - longterm	0	m
USIPTOT	US industrial production	1	m
AS5L0955R	Asia composite leading indicator (normalised)	1.5	m
AS5L0958R	Asia composite leading indicator (amplitude adjusted)	1.5	m
AS5L0959	Asia composite leading indicator (trend restored)	1.5	m
CHOL0955R	China composite leading indicator (normalised)	1.5	m
CHOL0958R	China composite leading indicator (amplitude adjusted)	1.5	m
CHOL0959	China composite leading indicator (trend restored)	1.5	m
EMOL0955R	Euro Area composite leading indicator (normalised)	1.5	m
EAOL0958R	Euro Area composite leading indicator (amplitude adjusted)	1.5	m
EAOL0959	Euro Area composite leading indicator (trend restored)	1.5	m
USOL0955R	US composite leading indicator (normalised)	1.5	m
USOL0958R	US composite leading indicator (amplitude adjusted)	1.5	m
USOL0959	US composite leading indicator (trend restored)	1.5	m
EMECOIN	Euro-Coin real time estimates	0	m
Composite			
BIRD	Earlybird	0.5	m
OL0958R	composite leading indicator (amplitude adjusted)	1.5	m
OL0959	composite leading indicator (trend restored)	1.5	m
OL0955R	composite leading indicator (normalised)	1.5	m
Government			
BU2064A	tax revenue - EU customs duties	1.5	m
BU2009A	tax revenue - income taxes, total	1.5	m
BU2001A	tax revenue - turnover tax	1.5	m
BU2002A	tax revenue - turnover tax on imports	1.5	m
BU2000A	tax revenue - turnover taxes, total	1.5	m
BU2085A	tax revenue - wage tax	1.5	m

Note: Monthly(m) and quarterly(q) indicators are used with a publication lag of 0 months up to 5 months.

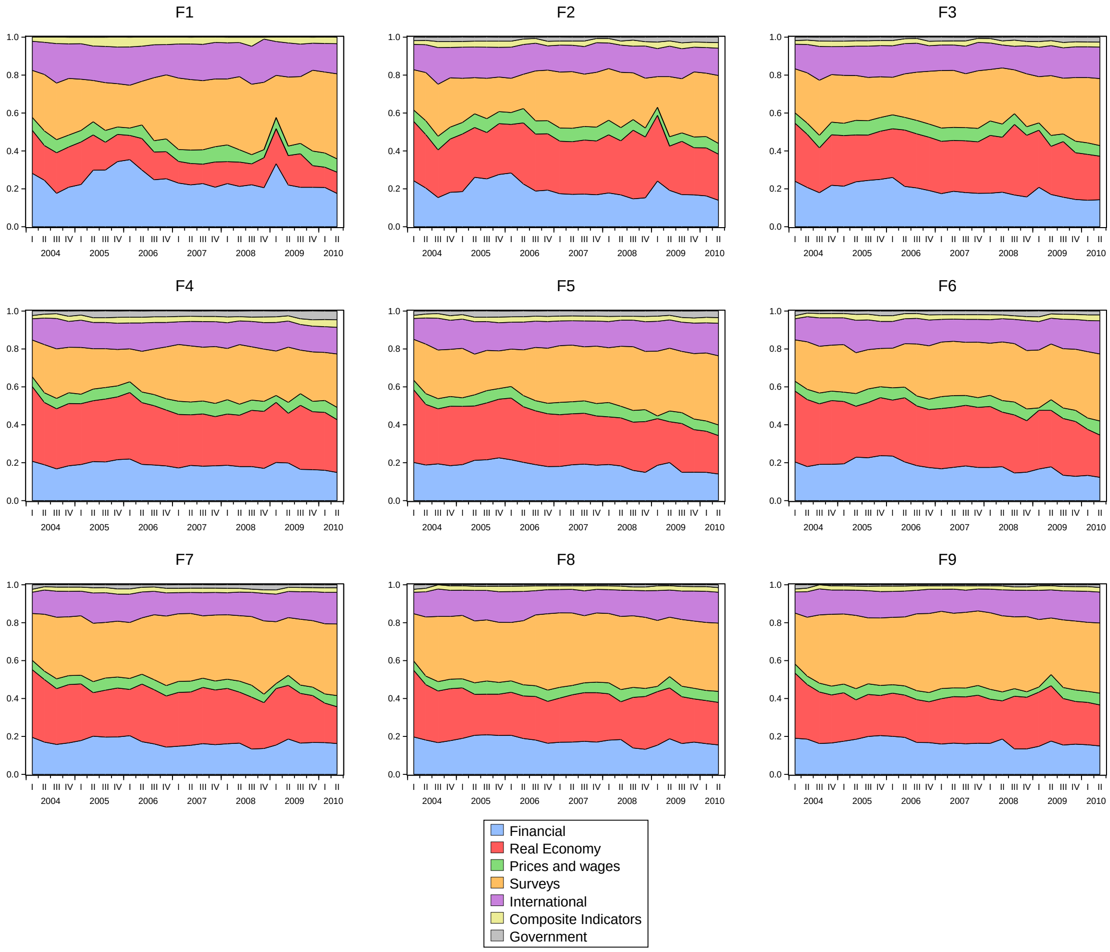
Table 6: GDP bottom-up forecast - demand approach

	F1	F2	F3	F4	F5	F6	F7	F8	F9
consumer expenditure									
AR	0.701	0.701	0.701	0.745	0.745	0.745	0.745	0.745	0.745
AIC	1.046	1.053	1.045	0.992	0.993	0.986	0.985	1.019	1.017
Wright2	1.139	1.144	0.979	1.089	1.091	1.125	0.892	0.941	1.154
mean	1.046	1.053	1.046	0.992	0.993	0.985	0.985	1.020	1.017
min AIC	0.980	0.975	1.078	0.991	1.042	1.128	0.953	0.953	1.077
gr	1.057	1.043	1.069	1.028	1.106	1.173	0.959	0.931	1.011
shrink	1.006	1.041	1.035	0.974	1.026	1.049	0.983	0.987	1.006
MMA	1.106	0.952	1.055	1.049	1.046	1.067	0.939	0.962	1.051
exports of goods & services									
AR	3.822	3.822	3.822	3.869	3.869	3.869	3.869	3.869	3.869
AIC	0.902*	0.903**	0.898**	0.908*	0.894*	0.891*	0.855*	0.844*	0.830**
Wright2	0.895	0.915	1.055	1.035	1.070	1.336	1.279	0.898	0.883
mean	0.903*	0.905**	0.901**	0.910*	0.896*	0.894*	0.859*	0.847*	0.834**
min AIC	0.992	0.833	1.006	0.932	0.893	0.744	0.755	0.743*	0.799
gr	0.967	0.932	0.904	0.969	0.955	0.983	0.952	0.940	0.984
shrink	0.917	0.889	0.877	0.892	0.887	0.882	0.864	0.883	0.895
MMA	1.018	1.092	1.164	1.107	1.083	0.878	0.877	0.935	0.949
imports of goods & services									
AR	3.277	3.277	3.277	3.194	3.194	3.194	3.194	3.194	3.194
AIC	0.865*	0.871**	0.849**	0.855**	0.856**	0.855**	0.846**	0.834**	0.824**
Wright2	0.919	1.024	0.950	0.905	0.892	0.934	0.936	0.971	0.933
mean	0.864**	0.871**	0.850**	0.856**	0.857**	0.856**	0.848**	0.835**	0.826**
min AIC	1.045	0.800*	0.882	0.922	1.043	1.035	1.053	0.882	0.847
gr	1.023	0.974	0.848	0.865	1.000	0.990	0.943	0.859*	0.834**
shrink	0.938	0.917	0.847*	0.878	0.907	0.921	0.914	0.858*	0.774***
MMA	1.018	0.863	0.901	0.831	0.936	1.009	0.900	0.847*	0.794**
government consumption									
AR	0.836	0.836	0.836	0.832	0.832	0.832	0.832	0.832	0.832
AIC	1.039	1.055	1.042	0.988	0.993	0.971	0.981	0.995	0.984
Wright2	1.170	1.233	1.142	1.096	1.110	1.070	1.003	1.010	1.050
mean	1.037	1.054	1.042	0.989	0.995	0.972	0.983	0.997	0.986
min AIC	1.060	1.412	1.365	1.293	1.194	1.088	1.349	1.270	1.025
gr	1.143	1.204	1.123	1.047	0.994	0.971	0.960	0.981	1.021
shrink	1.126	1.148	1.112	1.058	1.075	1.017	1.015	1.028	1.019
MMA	1.290	1.068	1.174	0.978	0.986	0.992	0.972	0.982	1.007
construction investment									
AR	3.300	3.300	3.300	3.277	3.277	3.277	3.277	3.277	3.277
AIC	0.991	0.988	0.970	0.955	0.942*	0.947*	0.945*	0.936*	0.945*
Wright2	1.049	1.041	1.027	1.055	1.097	1.183	1.134	1.081	1.047
mean	0.992	0.988	0.969	0.956	0.944*	0.949*	0.947*	0.938*	0.945*
min AIC	1.054	1.104	1.086	0.973	0.905	0.905	0.869	0.869	0.987
gr	1.053	1.061	0.962	0.966	0.692***	0.753***	0.731**	0.725**	0.901
shrink	1.029	1.036	0.945	0.925	0.735**	0.783**	0.769**	0.761**	0.887
MMA	0.966	1.029	0.991	0.922	0.825**	0.968	0.891	0.887	1.033
remaining gross fixed investment									
AR	4.818	4.818	4.818	4.859	4.859	4.859	4.859	4.859	4.859
AIC	0.935*	0.932*	0.914*	0.937*	0.920*	0.916*	0.887**	0.888*	0.873**
Wright2	1.129	0.985	0.989	1.081	0.952	0.998	1.039	0.958	0.941
mean	0.934*	0.932**	0.915*	0.938*	0.921*	0.917*	0.890**	0.890*	0.875**
min AIC	1.344	1.300	1.281	0.991	1.324	1.368	1.388	1.394	1.339
gr	1.219	1.010	0.997	1.020	0.996	1.103	1.029	0.933	0.812**
shrink	1.090	1.006	0.968	0.972	0.948	0.965	0.925	0.915	0.871*
MMA	1.172	1.104	1.112	1.060	0.925	1.040	0.875*	0.891	1.107
inventories									
AR	5.420	5.420	5.420	4.277	4.277	4.277	4.277	4.277	4.277
AIC	0.998	0.996	0.997	1.006	1.004	1.011	1.009	1.014	1.024
Wright2	1.060	1.074	1.104	0.989	1.056	1.057	1.055	1.065	1.081
mean	0.999	0.996	0.997	1.005	1.003	1.011	1.009	1.014	1.025
min AIC	1.061	1.200	1.027	1.125	1.126	1.135	1.105	1.130	1.138
gr	0.992	0.994	0.917	1.010	1.032	1.007	0.980	0.942	0.993
shrink	0.964	0.971	0.943	1.008	0.994	0.982	1.002	0.984	0.991
MMA	0.890**	0.924	0.949	1.014	1.023	1.022	1.029	1.060	1.014

Table 7: GDP bottom-up forecast - production approach

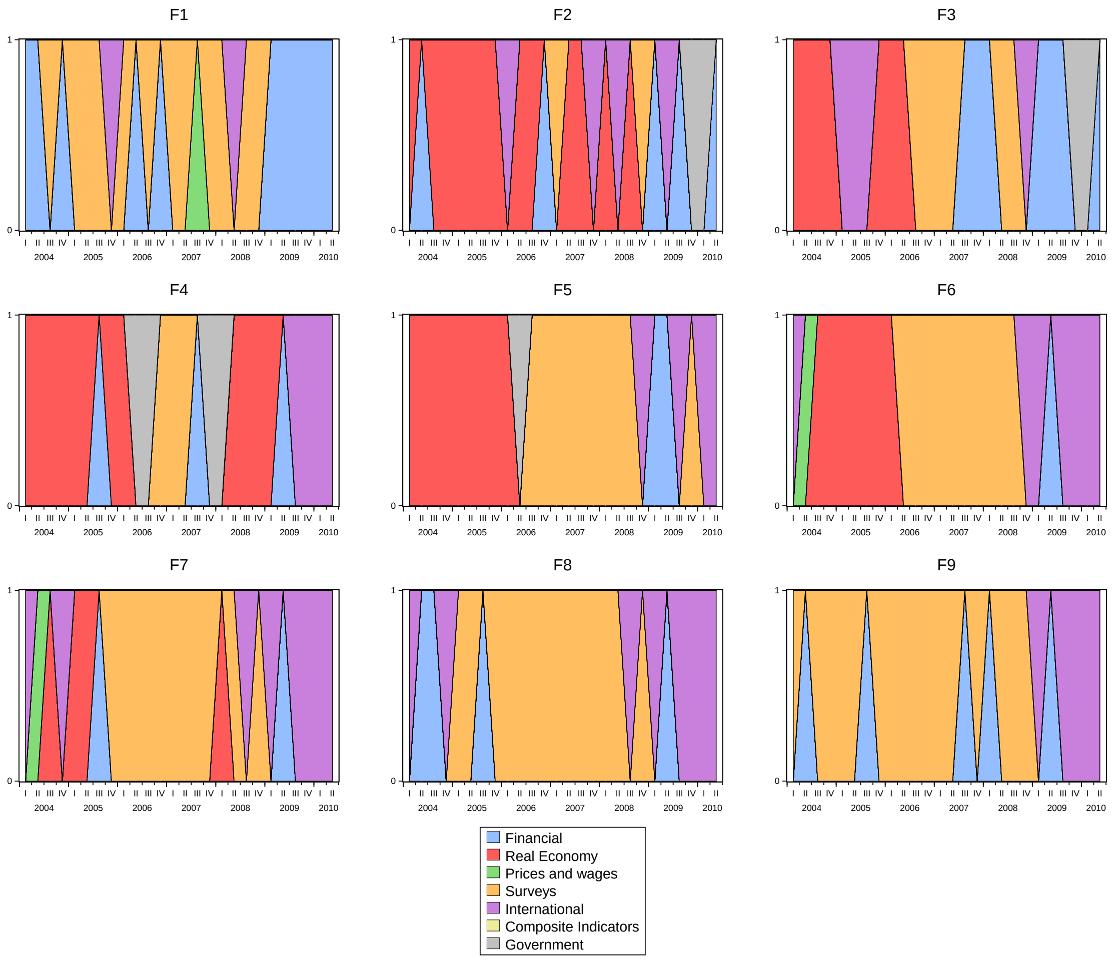
	F1	F2	F3	F4	F5	F6	F7	F8	F9
agriculture, forestry & fishing									
AR	6.563	6.563	6.563	6.592	6.592	6.592	6.592	6.592	6.592
AIC	1.018	1.022	1.017	1.007	1.003	1.008	1.033	1.039	1.028
Wright2	1.024	1.011	1.185	1.109	1.350	1.303	1.318	1.115	1.102
mean	1.018	1.022	1.017	1.007	1.003	1.008	1.033	1.040	1.029
min AIC	1.084	1.084	1.039	1.083	1.196	1.196	1.082	1.046	1.056
gr	0.985	1.008	1.050	1.031	1.075	1.056	1.071	1.046	1.061
shrink	1.001	1.041	1.038	0.996	1.052	1.047	1.080	1.063	1.043
MMA	1.012	1.080	1.095	1.040	1.078	1.077	1.028	1.029	1.028
construction									
AR	3.923	3.923	3.923	3.776	3.776	3.776	3.776	3.776	3.776
AIC	0.991	0.983	0.963*	0.956*	0.936**	0.954*	0.958*	0.952*	0.962
Wright2	1.097	1.127	0.980	1.064	1.172	1.200	1.223	1.240	1.048
mean	0.992	0.984	0.963*	0.955*	0.936**	0.955*	0.959	0.952*	0.962
min AIC	1.159	1.268	1.140	1.045	1.026	1.026	1.000	1.000	1.011
gr	1.024	1.065	0.902	0.925	0.864**	0.868*	0.946	0.990	1.049
shrink	1.018	1.046	0.926	0.936*	0.894**	0.903**	0.935*	0.961	1.011
MMA	1.009	1.021	1.009	0.983	0.953	1.028	0.968	0.963	1.105
financing,renting & corporate services									
AR	0.869	0.869	0.869	0.869	0.869	0.869	0.869	0.869	0.869
AIC	0.969	0.985	0.975	0.989	0.974	0.956*	0.957	0.944*	0.908**
Wright2	1.062	1.057	1.163	1.200	1.217	1.208	1.111	1.167	1.035
mean	0.969	0.985	0.975	0.988	0.973	0.956*	0.957	0.944*	0.908**
min AIC	1.205	1.237	1.308	1.333	1.143	1.158	1.007	1.152	1.175
gr	1.029	1.033	1.102	1.119	1.086	1.027	1.092	1.121	1.025
shrink	0.972	0.989	0.972	1.009	1.010	0.977	1.022	1.014	0.961
MMA	0.940	0.931	0.982	1.072	1.076	1.017	0.975	0.956	0.928
producing sector excl. construction									
AR	3.786	3.786	3.786	3.383	3.383	3.383	3.383	3.383	3.383
AIC	0.908*	0.902*	0.876**	0.965**	0.948**	0.928**	0.893**	0.874**	0.864**
Wright2	0.928	0.905	0.916	0.968	1.097	1.038	1.028	0.864**	0.858*
mean	0.909*	0.906*	0.881**	0.967**	0.950**	0.933**	0.899**	0.880**	0.871**
min AIC	0.893	0.747	0.751	0.804	0.819	0.750*	0.746*	0.671*	0.683*
gr	0.941	0.837	0.842	0.966	0.975	0.823**	0.837**	0.834**	0.863***
shrink	0.925	0.839	0.838	0.936**	0.930**	0.824**	0.814**	0.787**	0.789**
MMA	0.979	0.936	0.912	0.961	1.016	0.921*	0.963	0.846**	0.861**
public & private service suppliers									
AR	0.429	0.429	0.429	0.430	0.430	0.430	0.430	0.430	0.430
AIC	1.015	0.998	0.990	0.961	0.966	0.966	0.980	0.994	0.985
Wright2	1.526	1.504	1.064	1.184	0.983	0.999	1.067	1.092	1.150
mean	1.014	0.997	0.989	0.960	0.966	0.966	0.980	0.994	0.985
min AIC	1.048	1.128	1.122	1.251	1.221	1.114	1.095	1.180	1.125
gr	1.345	1.338	1.106	1.105	1.158	1.185	1.202	1.160	1.150
shrink	1.175	1.118	1.092	1.126	1.071	1.080	1.123	1.093	1.046
MMA	0.929	0.960	0.922	0.912	0.985	0.950	0.971	1.050	1.073
wholesale & retail trade & transport									
AR	1.537	1.537	1.537	1.598	1.598	1.598	1.598	1.598	1.598
AIC	0.969	0.966	0.954	0.945*	0.938*	0.934	0.911*	0.896*	0.881*
Wright2	1.179	1.179	1.098	1.072	1.108	1.176	1.065	1.069	0.965
mean	0.967	0.966	0.954	0.945*	0.938*	0.934	0.911*	0.897*	0.883*
min AIC	1.214	1.222	1.421	1.139	1.145	0.936	0.924	0.882	0.939
gr	1.163	1.083	1.016	1.077	1.088	0.955	1.005	0.927	0.962
shrink	1.150	1.091	0.995	1.021	1.011	0.948	0.944	0.897	0.916
MMA	1.164	1.029	0.982	0.885	0.930	1.006	0.964	0.877	0.908
taxes- subsidies									
AR	3.460	3.460	3.460	2.859	2.859	2.859	2.859	2.859	2.859
AIC	1.033	1.026	1.025	1.034	1.029	1.034	1.039	1.013	1.009
Wright2	1.016	1.038	1.149	0.977	0.919	0.936	1.072	1.047	1.090
mean	1.033	1.026	1.025	1.033	1.028	1.033	1.038	1.013	1.009
min AIC	1.354	0.942	1.143	1.697	1.238	1.245	1.312	1.002	1.009
gr	1.043	0.912	0.961	1.052	0.987	1.004	1.093	0.932	0.950
shrink	1.024	0.953	0.996	1.024	1.054	1.014	1.052	0.957	0.943
MMA	1.033	0.877	0.883	1.189	1.130	1.147	1.137	1.012	0.993

Figure 2: Weights by AIC



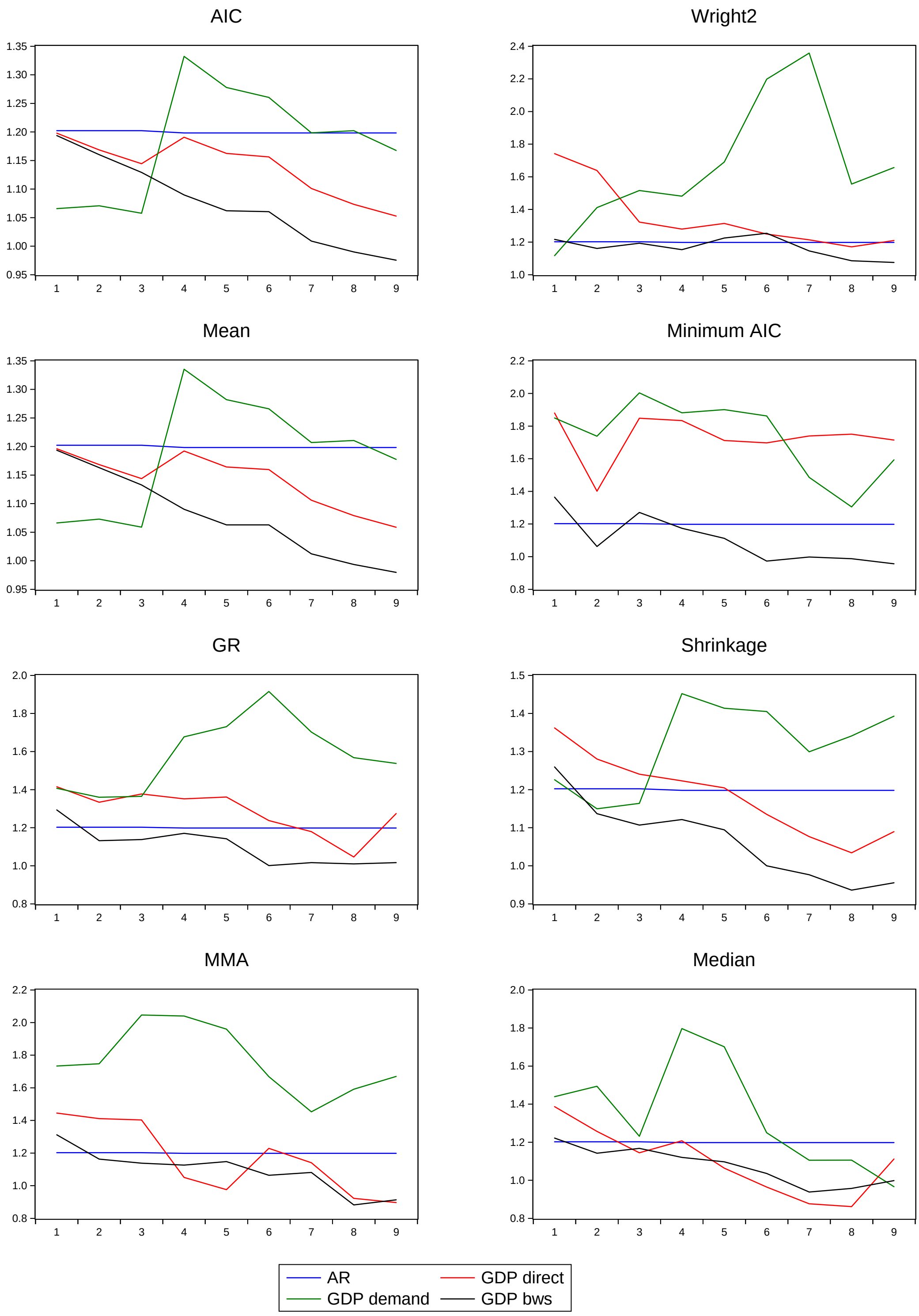
Note: Weights allocated to different blocks are shown for different forecast rounds.

Figure 3: Weights by min AIC



Note: Weights allocated to different blocks are shown for different forecast rounds.

Figure 4: RMSFE over Forecast rounds



Note: RMSFE for direct and bottom-up forecast are compared to the RMSFE of the AR-forecast for several weighting schemes.