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Bottom-up or Direct? Forecasting German GDP in a Data-rich Environment

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Bottom-up or Direct?
Forecasting German GDP in a Data-rich Environment

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Bottom-up or Direct? Forecasting German GDP in a Data-rich Environment*

Abstract

This paper presents a method to conduct early estimates of GDP growth in Germany. We employ MIDAS regressions to circumvent the mixed frequency problem and use pooling techniques to summarize efficiently the information content of the various indicators. More specifically, we investigate whether it is better to disaggregate GDP (either via total value added of each sector or by the expenditure side) or whether a direct approach is more appropriate when it comes to forecasting GDP growth. Our approach combines a large set of monthly and quarterly coincident and leading indicators and takes into account the respective publication delay. In a simulated out-of-sample experiment we evaluate the different modelling strategies conditional on the given state of information and depending on the model averaging technique. The proposed approach is computationally simple and can be easily implemented as a nowcasting tool. Finally, this method also allows retracing the driving forces of the forecast and hence enables the interpretability of the forecast outcome.

Keywords: contemporaneous aggregation, nowcasting, leading indicators, MIDAS, forecast combination, forecast evaluation

JEL Classification: E32, E37, C52, C53

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„Bottom-up“ oder direkt? Zur Prognose des deutschen Bruttoinlandsproduktes in einer datenreichen Umgebung

Zusammenfassung

Dieser Beitrag diskutiert eine Methode, frühzeitig die Wachstumsrate des deutschen Bruttoinlandsproduktes des laufenden Quartals zu bestimmen. Es werden MIDAS-Regressionen verwendet, um mit dem Problem unterschiedlicher Datenfrequenzen umzugehen. Zudem werden Pooling-Ansätze diskutiert, die den Informationsgehalt verschiedener Indikatoren effizient zusammenzufassen. Im Folgenden wird untersucht, ob es besser ist, das BIP zu disaggregieren (entweder über die Entstehungsseite oder über die Verwendungsseite) oder ob ein direkter Ansatz besser geeignet ist, das BIP-Wachstum zu prognostizieren. Das hier besprochene Vorgehen vereint eine große Anzahl von monatlichen und vierteljährlichen Indikatoren unter Berücksichtigung ihrer jeweiligen Veröffentlichungstermine. In einem simulierten Out-of-Sample-Experiment werden die verschiedenen Modellierungsstrategien bei unterschiedlichem Dateninformationsstand und je nach Prognosekombinationstechnik verglichen. Der vorgeschlagene Ansatz lässt sich leicht praktisch implementieren und kann als Prognosetool genutzt werden. Schließlich ermöglicht diese Methode sehr transparent, die treibenden Kräfte der Prognose nachzuvollziehen und ermöglicht somit die Interpretierbarkeit des Prognoseergebnisses.

Schlagwörter: kontemporäre Aggregation, Nowcasting, Frühindikatoren, MIDAS, Prognosekombination, Prognoseevaluation

JEL-Klassifikation: E32, E37, C52, C53

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 substantial publication lags. This implies that forecasting of economic variables is not merely concerned with predicting future economic developments, but rather with predicting the current situation (*nowcasting*, see, Banbura *et al.*, 2010) and the recent past (*backcasting*) since no official statistics are available for this period.

The problem of imperfect data knowledge is most evident for variables collected at low frequency. For instance, 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 corresponding quarter. Official Statistics for 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). A successful 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 (or jagged) edge data structures.¹

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 various forecasting rounds (twice a month) to simulate the forecasting process in pseudo real-time. Leading indicator regression models are employed, where each individual indicator is modelled separately. Afterwards, model averaging strategies (naive, in-sample and out-of-sample based weighting schemes) are applied to generate aggregate forecasts. Similar strategies have been undertaken by e.g. Angelini *et al.* (2011) and Drechsel and Maurin (2011) 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. Thus our objective is to analyze more

¹ According to their timeliness different variables will have missing observations at the end of the sample.

systematically the role of incoming data and new information to run pseudo real-time estimates of quarterly real GDP growth.

The main contribution 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 (i.e. by combining private consumption, investment, exports,...) or on the production side (i.e. by combining the gross value added of different sectors, e.g. production, construction, services,...). In the past decade the subject contemporaneous aggregation issues 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, e.g. Marcellino *et al.*, 2003). However, the effects of contemporaneous aggregation of (sub)components for time-series data in applied empirical work has not received much attention most recently.²

For forecasting (aggregate) GDP, the direct approach clearly dominates in the empirical literature on leading indicators (see, e.g. Stock and Watson, 2003; Banerjee *et al.*, 2005). Nevertheless, disaggregated approaches are also used occasionally in fore- and nowcasting exercises. For instance, Hahn and Skudelny (2008) pursue this line of research for the euro area or Barhoumi *et al.* (2011) for France. Moreover, for Germany the production-side approach is also preferred by 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. Using the demand side to model and forecast GDP is usually 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 by-product we also receive optimal forecasts (given the particular information set) for each GDP subcomponent. Additionally, with our forecasting set-up, 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 contain 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 5 supplement certain robustness checks. Finally, Section 6 concludes.

² An exception is Hubrich (2005), who investigates whether aggregating inflation forecasts based on HICP sub-indices is superior to forecasting aggregate HICP inflation directly.

2 Contemporaneous aggregation of GDP components

Generally, the relationship between GDP and a coincident or leading indicator can be modelled on different aggregation levels. Obviously, the simplest method is to relate GDP directly on the candidate indicator or alternatively, modelling subcomponents of GDP depending on the indicator and afterwards adding up all the subcomponents to an aggregate GDP forecast. Based on the national accounting methodology (see, 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 sectors).

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 or Grunfeld and Griliches 1960 for early contributions). Only under the assumption of a known data-generating process (DGP), it is well established that modelling the subcomponents and then aggregating the components does lead to lower mean squared forecast errors (MSFEs) relative to modelling the aggregate directly (see, e.g. Lütkepohl, 1984). Clearly this not much helpful for an 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 modelling the aggregate.

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

$$y_t^{agg} = w_{1t}y_{1t} + w_{2t}y_{2t} + \dots + w_{nt}y_{nt} \quad \text{for } t = 1, \dots, T, \quad (1)$$

where the y_{it} 's are the quarterly growth rates of the n subcomponents of y_t^{agg} compared to the previous quarter $\ln(Y_{it}/Y_{it-1}) * 100$, and the w_{it} 's are the corresponding aggregation weights. We allow the weights to be time varying to take into account changes in the composition of aggregate GDP and we assume that the weights add up to 1, i.e. $\sum_i w_{it} = 1$.³ We denote the direct forecast of the aggregate variable by \hat{y}_t and an indirect forecast of the aggregate variable computed by aggregating the disaggregated forecasts \hat{y}_{it} ($i = 1, \dots, n$) as $\hat{y}_{sub,t}^{agg} = \sum_i w_{it}\hat{y}_{it}$.

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

³ Note that we do not restrict the weights to be strictly positive, since the growth contribution of inventories might be also negative.

increasing variance by including additional parameters (Hendry and Hubrich, 2011). 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 like ours is raised by Hubrich (2005) who investigates the usefulness of disaggregating the HICP into its subcomponents and then compares the outcome of a direct approach with those of the disaggregate procedure. This study finds that disaggregation does often not result in lower forecast errors compared to directly modelling the aggregate inflation rate. Zellner and Tobias (2000) also investigate forecasts of GDP growth rates, but at an international level. They find that disaggregation of international forecasts on a country-level basis improves forecast accuracy, but only when also aggregate information (i.e. supranational variables) is used for the specification within countries.

Basically one would expect that a disaggregate approach for forecasting is advantageous whenever there exists 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 macroeconomic model with a simple production-side approach and pure time-series models for aggregate GDP. However, they do not take into account the full conjunctural information at each forecasting stage.

2.2 Practical implementation of aggregation

The gross domestic product, defined as the value of goods and services produced by a particular country in a given period, can be decomposed in various ways, such that the sum of the components equals the aggregate GDP.⁴ The two most popular decompositions include the production-side approach and the demand-side approach.⁵ 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 indicator forecasts are conducted by Parigi and Schlitzer

⁴ Note that due to the conversion of the national accounts system and the introduction of previous years prices, the real subcomponents do not necessarily sum to the aggregate quantity. To circumvent this problem, we assign the statistical discrepancies to one of the sub-components.

⁵ Additionally, production equals income and can thus be decomposed into different blocks of income.

(1995) for Italy, Baffigi *et al.* (2004) for the euro area and Golinelli and Parigi (2007) for the G7 countries. The main drawback of these studies is that they do not give an overall comparison between direct, demand-side and production-side forecast results.

Whether the direct forecast or one of the bottom-up procedures for predicting GDP is superior may depend on several factors: the degree of heterogeneity of different sectors (within the economy), the correlation between the indicators and the target variables, and the particular system of national accounts.⁶ Clements and Hendry (2011) investigate the relation of aggregate and disaggregate forecasts in different settings. From their research it follows that in cases where disaggregate components are volatile and difficult to predict, forecasting the aggregate should be preferred. On the other hand, if weights and the coefficients of the disaggregate models do not change much, disaggregation may produce better forecasts. This implies that from a theoretical point of view, a general conclusion is difficult to obtain and hence requires a case by case (or country by country) investigation.

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:

$$Y^{demand} = C + CG + IC + INC + INV + X - M,$$

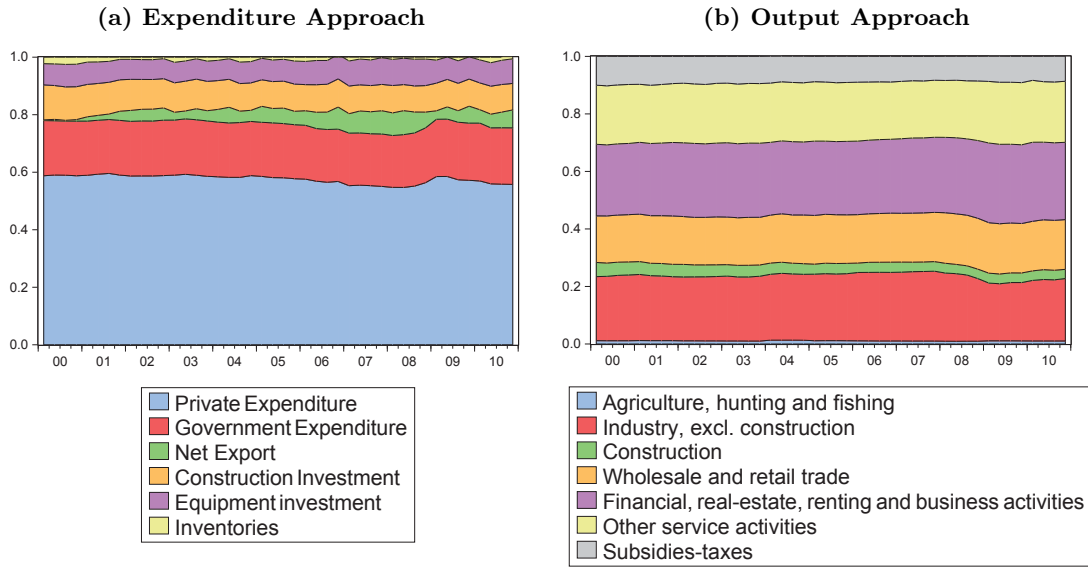
where the level of GDP (Y) consists of levels of private consumption (C), government consumption (CG), construction investment (IC), remaining gross fixed investment (INC), inventories⁷ (INV) and exports (X) minus imports (M). Note that we disaggregate gross fixed investment into two separate components because we expect that building investment (both residential and non-residential building investment) is driven by different factors than equipment investment. All quantities are measured as real, chain-linked quantities which are seasonally and calendar adjusted.

By far the largest subcomponent on the expenditure side is private consumption which constitutes about 58% of GDP in 2010 (see Figure 1a). 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. Germany runs a trade surplus the last years, hence the trade balance is positive and around 5% in real terms.

⁶ Most European countries employ a GDP measure which is primarily based on the production side, while the US GDP measure is focused on the demand side. Therefore, one would expect different implications for the predictive performance of leading indicators for the two bottom-up procedures.

⁷ Our measure of inventories is defined as real GDP minus final demand.

Figure 1: Share of GDP



Source: German Federal Statistical Office, author's calculation.

The corresponding GDP growth forecast from the expenditure side can be derived from the growth forecast of each component times the corresponding GDP share. This implies that $\hat{y}_{demand,t}^{agg} \approx \sum_i^n \hat{w}_{it} \hat{y}_{it}$, where \hat{y}_i is the growth forecast of the i th component (out of $n = 7$ components) and \hat{w}_{it} are the estimated weights. Since we apply real quantities, this relationship holds only approximately due to chained weighting.⁸ The weights are computed as a moving average of the 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 .⁹ This allows us to consider the time-varying composition of the expenditure shares due to both business cycle fluctuations and long-term developments.¹⁰

⁸ Since the introduction of prices of the preceding year as basis for calculating macroeconomic time series in real terms, the real GDP may deviate from the sum of real GDP components. This also implies that GDP growth may deviate from the contribution weighted sum of component growth rates. Since the deviations are extremely small relative to the forecast error, we can take this as a reasonable approximation.

⁹ Alternative methods for calculating the weights (based on nominal shares or by using an alternative moving-average scheme) has little effects on the results.

¹⁰ In the literature the GDP components are often simply weighted by their share in GDP over the total sample. In general, one could also get a forecast when all the different component forecasts are available. However, this is only possible when the previous growth rate is available (in the case of one step ahead predictions). When this is not the case it gets much more complicated. Therefore, we choose the moving average which was tested against forecasting the weights for the one-step ahead forecast. Due to the strong persistence of the GDP shares the two methods perform similarly.

The production-side approach

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

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

where the individual sectors constitute of manufacturing (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 are classified according to the NACE scheme (Nomenclature générale des activités économiques dans les Communautés Européennes). Again the analysis relies on quarterly seasonal and calendar adjusted real quantities.

The largest share in production is captured by the services sector. Financial, real estate, renting and business services, and public and other services account for approximately 27% and 21% of total production, respectively (see Figure 1b), followed by the manufacturing sector (excl. construction) with 21% which is relatively high for an industrialized 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, i.e. taxes minus subsidies, contributes to 9% of total growth.¹¹ Similar to the demand components, the growth rate of each supply-side 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 recent share in GDP.

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 has to be considered. Then econometric models have to be specified to account for 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.

¹¹ Similar to the demand components, the components of the production side do not sum up to real GDP. Therefore we treat the variable taxes minus subsidies as our residual which also reflects the statistical discrepancies due to chain weighting.

3.1 Data set

Our data set contains 273 indicators on monthly or quarterly frequency which are published primarily by the German Federal Statistical Office or Deutsche Bundesbank (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 (12) contain consumer prices, producer prices, export and import prices, commodity prices and wholesale prices. For survey data, we use 79 series comprising 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 (29) 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). Furthermore, 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 levels, differences or log-differences are used.¹² An important issue for simulating realistic forecasting settings is to take into account the publication lags of relevant leading indicators.¹³ 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 endogenous variable, the available data set will continuously vary due to manifold lags in publication of the respective indicators. For an applied economic 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 first GDP estimate (flash) is published (45 days after the end of the reference quarter). Therefore, nine forecasts are generated at bi-weekly frequency using all available information.

¹² 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. Results are available upon request.

¹³ Note that we are using actual data that do not take into account the effects of data revisions (“pseudo real time data”).

Figure 2: Data releases and forecasting rounds

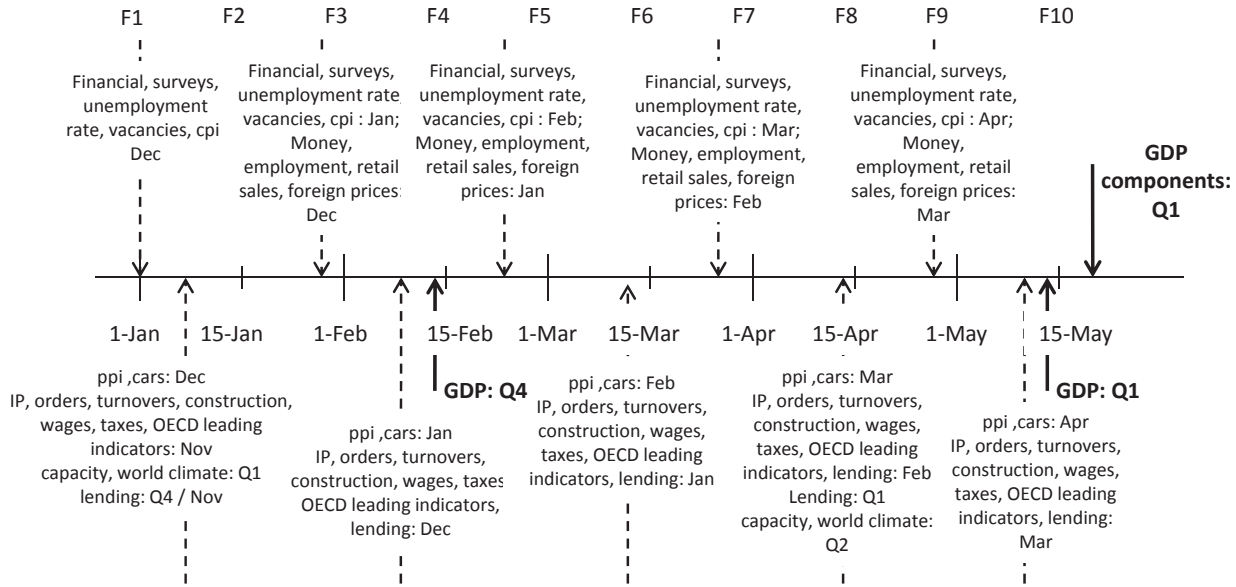


Table 2 shows the structure of our pseudo real-time forecasting exercise for the first quarter as an illustration. Starting with the first forecast, i.e. at the beginning of the first month of a quarter (e.g. January 1st), our data set includes monthly indicators that are early available in time (e.g. 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. The last forecast round (F9) is conducted before the flash estimate is published by the German Federal Statistical Office.

3.2 Single Model specifications

A further complication of the analysis derives from the fact that many leading indicators are available at monthly frequency whereas the target variable, GDP growth, is only at hand at quarterly frequency. 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, e.g. Kitchen and Monaco, 2003). However, the optimal conversion method is generally unknown and may vary from one forecasting round to the next.¹⁴ Therefore, Schumacher and Breitung (2008), Aruoba and Diebold (2010), Banbura *et al.* (2011)

¹⁴ 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.

and Angelini *et al.* (2011) 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.

An alternative framework has been proposed by Ghysels *et al.* (2004); Andreou *et al.* (2011) and has been recently applied by Clements and Galvão (2009) and Marcellino and Schumacher (2010) to macroeconomic forecasting. We follow their procedure which is called MIXed DATA Sampling (henceforth MIDAS) regression models and is meant to circumvent the problems of quarterly conversion. 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 changes in the explanatory variables. This 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 a highly parameterized dynamic model. The main advantage is that for the distributed lag specification only a small number of parameters has to be estimated although long lags can be captured.

The standard MIDAS model with a single explanatory variable and for given state of information l can be described by

$$y_t = \beta_0 + B(L^{1/m}; \theta)x_{t-l}^{(m)} + \epsilon_t^{(m)} \quad (2)$$

where $B(L^{1/m}; \theta) = \sum_{k=1}^K b(k; \theta)L^{(s-1)/m}$ and $L^{s/m}x_{t-1}^{(m)} = x_{t-1-s/m}^{(m)}$. t is the time index of interest (in our case, quarters), m is the higher sampling frequency (i.e. $m = 3$ for monthly data), s is a continuous index ($s = 0, 1, 2,$) and K is the maximum number of lags. We parameterize $b(k; \theta)$ as an Almon-Distributed Lag model which is estimated with a restricted least squares approach and can be represented as:

$$b(k; \theta) = \theta_0 + \theta_1 k + \theta_2 k^2 + \dots + \theta_q k^q, \quad (3)$$

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.¹⁵ In many applications, a relative small number for q is sufficient to allow for a flexible adjustment. In practice one has to make a choice

¹⁵ Note that by applying the standard Almon-Distributed Lag model, we deviate from the existing literature, since most applications utilize the Exponential Almon Lag model where the weights are always positive: $b(k; \theta) = \frac{\exp(\theta_1 k + \theta_2 k^2)}{\sum_{k=1}^K \exp(\theta_1 k + \theta_2 k^2)}$. This restriction is sometimes necessary, e.g. for GARCH models where negative weights are undesirable. 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.

for q and K . We use information criteria, namely the SIC, to evaluate different combinations of q and K for the in-sample period and choose the one that optimizes the Schwarz criteria.¹⁶

In the MIDAS specification (eq. 2) the target variable y_t is directly related to information available at period $t - l$. l does therefore reflect the exact state of monthly information ($l = 0, \frac{1}{3}, \frac{2}{3}, \frac{3}{3}, \dots$). This 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 l is specified. Under the assumption that one month of the actual quarter is already available, $K = 12$ (one year of information), and $m = 3$ (three observation within one quarter) the MIDAS regression model equals

$$y_t = \beta_0 + B(L^{1/3}; \theta)x_{t-2/3}^{(3)} + \epsilon_t^{(3)}, \quad (4)$$

so that

$$y_t = \beta_0 + b(0; \theta)x_{t-2/3}^{(3)} + b(1; \theta)x_{t-1}^{(3)} + b(2; \theta)x_{t-1-1/3}^{(3)} + \dots + b(K; \theta)x_{t-4-1/3}^{(3)} + \epsilon_t^{(3)}. \quad (5)$$

According to Clements and Galvão (2009) one may also include autoregressive dynamics into the model. Therefore, we also consider the following model

$$y_t = \lambda y_{t-h} + \beta_0 + B(L^{1/3}; \theta) (1 - \lambda L^1) x_{t-l}^{(3)} + \epsilon_t^{(3)}. \quad (6)$$

Whether the standard or autoregressive augmented version is used is decided according to the SIC. Note that the lag of the endogenous variable (h) depends on the exact state of information and varies between 1 (when the previous value is available) and 2 (when the previous value is still unavailable). This also makes the difference between a one-step ahead and a two-step ahead forecast.

While the MIDAS approach is employed for the indicators available at monthly frequency, we also take into account information sampled at quarterly frequency. Therefore we use a standard autoregressive distributed lag (ARDL) approach (following Stock and Watson, 2003) for the quarterly indicators:

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

¹⁶ We select K among 9 and 12 months and take into account q between 1 and 3. We also experimented with higher polynomials and longer lags, but did not find much improvement.

where u_t is an error term and α , β and γ are regression coefficients to be estimated. k and l reflecting potential publication lags of the indicators as well as of the dependent variable. Again, the respective lag lengths p and q are selected by SIC. Starting from an estimation sample 1992q1-2003q4 the rolling estimation window moves up to final quarter 2010q4. For the 9 different states of available information the indicator models are reselected and reestimated.

3.3 Model combination

While some single indicator models may already provide good forecast accuracy, it is generally 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 of information by employing only 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.¹⁷ The literature has shown that the combination of forecasts often results in an improvement of forecast accuracy compared to univariate benchmark models or to a single modelling 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, 2012b, before and during the financial crisis). In our application we take into account a large set of pooling techniques that combine the forecasts based on MIDAS models (where monthly indicators are available) with those based on standard ARDL models (for quarterly indicator variables). While there have been some work on the combination of MIDAS-model forecasts (see, Clements and Galvão, 2009; Kuzin *et al.*, 2009; Andreou *et al.*, 2010), a more systematical and more complete assessment is still missing. Therefore, we conduct a comparison of pooling techniques for MIDAS models that also takes into account the different states of data availability.

Pooling the individual indicator forecasts $\hat{y}_{i,t}$ we obtain the total forecast \tilde{y}_t by:

$$\tilde{y}_t = \sum_{i=1}^n \omega_{i,t} \hat{y}_{i,t} \quad \text{with} \quad \sum_{i=1}^n \omega_{i,t} = 1 \quad (8)$$

where $\omega_{i,t}$ is the weight assigned to each indicator forecast that results from the fit of the i^{th} individual equation. Note that due to the subscript t we allow for time-varying weights. n_t is the total number of models retained at time period t .¹⁸ Model averaging can be both employed for the direct GDP forecasts as well as for the individual GDP components either through the

¹⁷ Table 6 in the appendix indicates the average number of indicators that are used at each forecasting round to generate a pooled forecast.

¹⁸ According to the recursive model selection scheme of each indicator model, only those models survive for the model averaging scheme that obtain a smaller SIC than the AR-model (which exclusively consists of a constant and its own lags).

supply or the demand side. To arrive at the final combined forecast given the individual forecasts from the various models, one has to specify the exact model weight.

A very simple but often effective way is to employ the same weight to each model ((*i*) mean, $w_i = 1/n$). Despite its simplicity, it has been found that the equal weighting scheme is hard to beat in practice (see, Timmermann, 2006) and thus serves a natural benchmark for other more sophisticated weighting schemes.¹⁹

Combination according to in-sample information

The in-sample information of each indicator model provides a very natural base for computing the weights attached to each model. A simple procedure which 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) and Drechsel and Maurin (2011). Intuitively the model with the lowest SIC receives the highest weight. A very restrictive special case of an in-sample weighting scheme is to select the model which fits best during the in-sample period. This corresponds to a model selection problem where one model gets a weight of unity whereas the remaining models obtain zero weights. More specifically, at each point in time we select the model which obtains the smallest SIC ((*ii*) minSIC).

In general Bayesian Model Averaging (BMA) methods offer an attractive framework for obtaining the model weights to the individual forecasts (see, Kapetanios *et al.*, 2008; Wright, 2008; Faust *et al.*, 2011; Drechsel and Scheufele, 2012b, for application in economic forecasting). Typically, one assumes that the distribution of y_t conditional on a matrix of potential covariates x_{t-1} is given by one of n models, denoted by M_1, \dots, M_n (see, Stock and Watson, 2006, section 5).²⁰ Then the predictive probability density of y_t is given by

$$f(y_t|D_{t-1}) = \sum_{i=1}^n f_i(y_t|D_{t-1})\Pr(M_i|D_{t-1}), \quad (9)$$

where $f_i(y_t|D_{t-1})$ is the predictive density of y_t for model i and $\Pr(M_i|D_{t-1})$ is the posterior probability of model i . This implies for the optimal Bayes forecast of the conditional mean of y_t (under squared loss) which can be denoted by $\tilde{y}_{t|t-1}$ that the posterior mean is a weighted sum the individual model's forecasts, given by

¹⁹ We also consider the median as an alternative to the arithmetic mean, which is supposed to be more robust to outliers.

²⁰ We follow Kapetanios *et al.* (2008) and Drechsel and Scheufele (2012b) and look for the optimal combination of single indicator models. Thus we do not take into account all possible indicator combinations in the model averaging procedure (which would be impossible due to the high dimensionality of possible predictors).

$$\tilde{y}_{t|t-1} = \sum_{i=1}^n \Pr(M_i|D_{t-1})\tilde{y}_{M_i,t|t-1}, \quad (10)$$

where $\tilde{y}_{M_i,t|t-1}$ is the posterior mean of y_t of model M_i . By employing the g -prior methodology and by specifying a prior model probability of $\pi(M_i) = 1/n$, which implies that each model deemed to be equally likely before estimation. Then one obtains the (iii) bayesian weights as

$$\begin{aligned} \tilde{Y}_{t|t-1} &= \sum_{i=1}^n \omega_i \tilde{Y}_{M_i,t|t-1}, \\ \text{where } \omega_i &= \frac{(1+g)^{-k_i/2} \left[1 - \frac{g}{1+g} R_i^2\right]^{-(T-1)/2}}{\sum_{j=1}^n (1+g)^{-k_j/2} \left[1 - \frac{g}{1+g} R_j^2\right]^{-(T-1)/2}}, \end{aligned} \quad (11)$$

where R^2 is the coefficient of determination and k is the number of parameters of model i or j , respectively. This implies that the BMA weights depend on the in-sample fit of each model. Further, equation (11) includes a penalty term which penalizes models with more parameters through the $k/2$ exponent. The whole expression depend on the hyperparameter g that controls the degree of shrinkage. The larger g the closer follow the weights the model's in-sample fit. We specify g as a *unit information prior* which implies $g = T$ for a given sample size T .²¹ Note that BMA weights do not take into account the correlations between forecasts.

The assumption of zero correlation between forecasts can be empirically hardly justified and thus offers theoretically room for improving the forecast quality. 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). We implement the (iv) GR weighting scheme by solving the quadratic minimization problem:

²¹ This prior specification implies that the model weights are very smooth and not too far away from the equal weighting scheme. It can be related to the Bayesian or Schwarz information criterion and corresponding weights can be approximated by a smoothed version, namely $\omega_i^{SIC} = \frac{\exp(-0.5 \cdot \Delta_i^{SIC})}{\sum_{i=1}^n \exp(-0.5 \cdot \Delta_i^{SIC})}$ with $\Delta_i^{SIC} = SIC_i - SIC_{\min}$. Burnham and Anderson (2004) and Kapetanios *et al.* (2008) propose to use the Akaike (AIC) criterion instead of SIC. In this application we compute the Bayesian weights according to eq. (11). As a robustness check we also employ the smoothed SIC version as well as AIC weights and weights based on the R^2 . All methods produce similar results.

$$Q = (y - F\omega)'(y - F\omega), \quad (12)$$

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 all the models in-sample predictions at a given point in time and y is the target variable to be forecasted (past realizations). The weights are obtained by $\hat{\omega} = \text{argmin } Q(\omega)$ 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 overparameterisation when the number of predictors is high in relation to the sample size which results in high uncertainty of the estimated weights.²²

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

$$\hat{\omega} = (F'F + \gamma I)^{-1}(F'y + \gamma\mu), \quad (13)$$

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 Bayesian methods the shrinkage parameter is estimated as:

$$\hat{\gamma} = \hat{\sigma}^2 / \hat{\sigma}_\omega^2, \quad (14)$$

where

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

$\hat{\sigma}^2$ is the mean square error under OLS weights and $\hat{\sigma}_\omega^2$ is the ratio of the fitted regression variance and the average variance of the forecasts. The shrinkage parameter γ gets large when the variance

²² In order to reduce the uncertainty of the estimated weights, we also take into account an approximation of the covariance structure in the spirit of Figlewski (1983) and Ledoit and Wolf (2003) where it is assumed that the individual model forecasts can be characterized by a common factor structure, which is given by $e_{it} = \alpha_i + \beta_i f_{et} + \epsilon_{it}$. Estimating this equation for each model residual by OLS, one can then compute the approximated covariance matrix as $\hat{\Sigma}_{ef} = \hat{\sigma}_{fe}^2 \hat{\beta} \hat{\beta}' + \hat{D}_\epsilon$, where σ_{fe}^2 is the variance of f_{et} , $\hat{\beta}$ are the estimated factor sensitivities and \hat{D}_ϵ is a diagonal matrix with the estimated variances of the ϵ_{it} 's on the diagonal. Due to the diagonal assumption this estimate may be biased, but it requires much less parameters to be estimated. The results on this procedure are available on request.

of the forecasts is large or when the R^2 given the OLS weights is small. Computationally the shrunk weights ((v) shrink) are obtained by minimizing

$$Q = \frac{(y - F\omega)'(y - F\omega)}{\hat{\sigma}^2} + \frac{(\omega - \mu)'(\omega - \mu)}{\hat{\sigma}_\omega^2}, \quad (15)$$

subject to the same constraints as discussed for eq. (12).

As a third model averaging scheme employing the full in-sample covariance information, we consider Mallows Model Averaging ((vi) 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 can be done by minimizing the function

$$C = (y - F\omega)'(y - F\omega) + \omega' K s^2, \quad (16)$$

where K is a vector including the number of coefficients of each model and $s^2 = \frac{\hat{e}^{(M)'}\hat{e}^{(M)}}{T-k(M)}$ is an estimate σ^2 from the model with the smallest estimated error variance. Again, we apply 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.

All in-sample combination methods discussed so far are employed in each estimation stage (and thus optimized at each forecast step) which implies that the weights (ω) are allowed to vary over time (see, e.g., Figure 3). Due to the rolling estimation scheme employed for our models this may partly guard against instabilities over time.

Combination according to the out-of-sample performance

Forecast combination weights can be also obtained by referring to previous out-of-sample forecast errors. Since good in-sample fit of a model does not necessary translate into reliable out-of-sample performance. Particularly in cases where structural instabilities exist, the link between in-sample measures and out-of-sample precision may be distorted. Therefore, it can be advantageous to use the past forecast errors to compute the model weights. In doing so, we take into account the quasi real-time setting where the information in past forecast errors can only be employed when the forecasts and realizations are observed (so we consider a potential information lag). For instance, we observe GDP only with some time lag and when the new forecast is made only some past forecast errors are known. We can therefore only include forecast errors until $t - h$ ($h = 1$ and $h = 2$ for one and two step ahead forecasts, respectively). It also implies that, for the first few runs – when there is no out-of-sample information available –

we have to use the equal weighting scheme until the first past forecasts can be compared with their corresponding realization.

First, we employ weights that are inversely proportional to their past mean square forecast errors (*vii*) msfe). This procedure implies that those models obtain greater weights which were more accurate in the past. Additionally, to take into account some time-variation in forecasting performance, the most recent model behavior is weighted more heavily than those in the far past. This is ensured by using some form of discounting (see, Bates and Granger, 1969). Weights based on discounted mean square forecast errors (MSFEs) have been applied quite successfully by Stock and Watson (2004) and Drechsel and Scheufele (2012b) for output predictions based on leading indicators. More specifically, discounted mean square forecast error weights are based on

$$\omega_{i,t} = \frac{\lambda_{it}^{-1}}{\sum_{j=1}^n \lambda_{jt}^{-1}} \quad (17)$$

where $\lambda_{it} = \sum_{s=T_1}^{t-h} \delta^{t-s} (\hat{e}_{i,s})^2$ with δ being the discount factor and $\hat{e}_{i,s}$ the forecast error of model i .²³ 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. We set $\delta = 0.6$ which implies a moderate degree of discounting.²⁴

A weighting scheme that is often neglected in the literature is based on ranks (*viii*) (see, Timmermann, 2006). It is thus closely related to the previous combination scheme, but the weights are assigned according to the model ranks instead of the precise MSFEs. This implies that S_{it} is the recursively computed mean square forecast error of model i which is computed as $S_{it} = \sum_{s=T_1}^{t-h} (\hat{e}_{i,s})^2$. For each model, i , the rank for a h -step ahead forecast up to time t is then assessed by $\mathcal{R}_{t,t-h,i} = f(S_{1t}, \dots, S_{nt})$. The model with the best MSFE forecasting performance, gets a rank of 1, the second best a rank of 2 and so on.²⁵ The individual weights are then calculated as

²³ Since the number of models retained varies with each forecast round, we only consider those models for the MSFE weighting scheme that are actually different from the AR model. This implies that we then set $\lambda_{it}^{-1} = 0$.

²⁴ The optimal degree of discounting (which controls the degree of time variation of the weights) is generally unknown. Most of the literature tends to set δ between 0.9 and 1 (see, Stock and Watson, 2004), but also very low values of δ of about 0.3 are found to work well (e.g. Drechsel and Scheufele, 2012b). In general the optimal δ depends on the stability of the models under investigation. In our study the relative performance of MSFE weighting is not much affected by the choice of δ .

²⁵ Note that for the rank-based method we assume long memory so that all forecast errors are treated equally. Additionally, no model is excluded from the analysis even when it is identical with the AR model. For those models that get the same MSFE, we apply the average rank to every entity.

$$\omega_{i,t} = \frac{\mathcal{R}_{i,t-h}^{-1}}{\sum_{j=1}^N \mathcal{R}_{j,t-h}^{-1}}. \quad (18)$$

One advantage of ranks compared to direct MSFE-weights is that they are less sensitive to outliers and thus should be more robust.

So far we have discussed out-of-sample criteria that take into account the precision of the models past performance. However neither MSFE-weights nor rank-based weights regard the correlation structure of forecast errors. Thus similar to in-sample weighting procedures theoretically optimal weights can be computed using the Granger-Ramanathan procedure based on past forecast errors (*(ix)* egr). This procedure is complicated by the high dimensionality and by the fact that the forecast errors become available only recursively (which implies a small number of observations). Therefore, we modify the procedure and take only a small number of models that perform best in the past (those that obtain the lowest rank). Then we compute optimized weights similar to eq. (12) where the in-sample prediction F is replaced by the pre-selected out-of-sample errors.²⁶

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 a 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 again – according the state of information – 9 forecasts for 2004q2. This procedure is repeated until 2010q4 where the last forecasts are obtained. The employed procedure employs recursive forecasts by adopting a rolling window where the size of 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 relative to a benchmark model (simple univariate time-series model). The latter is a forecast from an univariate autoregressive model which corresponds to forecasts from eq.(7), where no further indicator x is specified.

We denote $\hat{y}_{i,t}^{\mathbf{m}}$ as forecasts based on the model combination scheme \mathbf{m} obtained for GDP forecast or for each GDP component i for period t . The corresponding forecast error is defined by the

²⁶ As more and more realised forecast errors get available, we can augment the total number of potential models recursively. We take $N_t = \min(\sum_{s=T_1}^{t-h} 3/4(t - T_1), 14)$ of the top performing models for calculating the regression weights (and for the first $3 + h$ rounds we apply the equal weighting scheme due to high estimation uncertainty). Additionally, we consider shrinkage to equal weights on the pre-selection, but this modification does not have much impact on the results.

difference between the realization $y_{i,t}$ and the forecasts ($\hat{e}_{i,t}^{\mathbf{m}} = y_t - \hat{y}_{i,t}^{\mathbf{m}}$). Similarly, $\hat{y}_{i,t}^{\mathbf{AR}}$ is the pure AR-forecast and $\hat{e}_{i,t}^{\mathbf{AR}}$ the corresponding forecast error. One obvious way to evaluate the forecast accuracy of a candidate model or a forecast combination procedure (\mathbf{m}) is to calculate relative RMSFEs (relative to the benchmark) given by

$$\text{relative RMSFE}^{\mathbf{m}} = \frac{\sqrt{\sum_{t=T_1}^{T_2} (y_{i,t}^{\mathbf{m}} - \hat{y}_{i,t}^{\mathbf{m}})^2}}{\sqrt{\sum_{t=T_1}^{T_2} (y_{i,t}^{\mathbf{m}} - \hat{y}_{i,t}^{\mathbf{AR}})^2}} = \frac{\sqrt{\sum_{t=T_1}^{T_2} (\hat{e}_{i,t}^{\mathbf{m}})^2}}{\sqrt{\sum_{t=T_1}^{T_2} (\hat{e}_{i,t}^{\mathbf{AR}})^2}}, \quad (19)$$

where T_1 indicates the first date of the pseudo out-of-sample forecast and T_2 is the 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 pure 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. Since the comparison of forecast errors in our setting involves models with estimated parameters, inference on these models may be complicated, particularly when models under investigation are nested (see, West, 1996). Therefore, we can stick to Giacomini and White's (2006) predictive ability test framework which only requires a rolling estimation scheme. This framework makes statements about forecasting methods rather than forecast models and makes it possible to compare different modeling procedures like the model averaging schemes (where it is sometimes unclear whether the models are nested or not). The test of equal unconditional predictive ability relies on

$$H_0 : E \left[(y_{i,t} - \hat{y}_{i,t}^{\mathbf{m}})^2 - (y_{i,t} - \hat{y}_{i,t}^{\mathbf{AR}})^2 \right] = 0.$$

The test statistic is

$$Z = \frac{(T_2 - T_1)^{-1} \sum_{t=T_1}^{T_2} \left[(y_{i,t} - \hat{y}_{i,t}^{\mathbf{m}})^2 - (y_{i,t} - \hat{y}_{i,t}^{\mathbf{AR}})^2 \right]}{\hat{\sigma} / \sqrt{T_2 - T_1}} \quad (20)$$

where the average loss differential is divided by the standard error. $\hat{\sigma}^2$ is a HAC estimator of the asymptotic variance. The test statistic Z can be evaluated against a standard normal distribution.

The finding that a model produces on average smaller forecast errors than one or more rival models does not necessary imply that a given forecast is optimal. A more demanding alternative is the notion of conditional efficiency (see, e.g. Granger and Newbold, 1977). This definition implies that a forecast is said to be conditionally efficient if the variance of the forecast error from a combination of the forecast with one or more rival forecasts is not significantly less than the original alone (Clements, 2004). This is the *encompassing* principle applied to forecast

evaluation. In our setting we are interested whether the supply and/or the demand-side approach contains any information beyond that already contained in the direct approach. Under squared loss, the direct forecast \hat{y}_t^{direct} is said to be conditional efficient with respect to the production-side forecast \hat{y}_t^{supply} and the demand-side forecast \hat{y}_t^{demand} for each forecast combination scheme \mathbf{m} if

$$E \left[(y_t - \hat{y}_t^{direct})^2 \right] \leq E \left[\left(y_t - (\lambda_1 \hat{y}_t^{supply} + \lambda_2 \hat{y}_t^{demand} + (1 - \lambda_1 - \lambda_2) \hat{y}_t^{direct}) \right)^2 \right]. \quad (21)$$

Interpreting the conditional expectations as a prediction links the encompassing approach to the general framework of predictive ability tests as proposed by Giacomini and White (2006). In their definition the forecasts depend on the parameter estimates at time t , rather than on population values (as discussed by Giacomini and Komunjer, 2005, for encompassing tests). The test can be conducted based on the models prediction errors in the augmented version of Harvey *et al.* (1998) given by the test regression:

$$\hat{e}_t^{direct} = \lambda_1 \left(\hat{e}_t^{direct} - \hat{e}_t^{supply} \right) + \lambda_2 \left(\hat{e}_t^{direct} - \hat{e}_t^{demand} \right) + v_t \quad (22)$$

for each weighting scheme \mathbf{m} . The corresponding null hypothesis equals

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

and is tested by a Wald test using HAC standard errors. Whenever the 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 presents the results on our proposed procedure for nowcasting of GDP growth. In the following we compare various weighting schemes for direct and disaggregated forecasting approaches. Forecasts for GDP growth are made at 9 different forecasting steps (bi-weekly) which reflects the flow of conjunctural information until the first GDP estimate is released by the federal statistical office. We also report the results for the individual GDP components using various model averaging schemes. Finally, we compare the direct approach with the production and expenditure approach based on the respective forecasting accuracy.

4.1 GDP Forecasts obtained with the direct approach

Table 1 shows the forecasting results based on the direct approach by using different combination schemes. As expected, the average forecast error decreases for most pooling techniques as more and more information becomes available and can be employed. Depending on the averaging scheme, the typically improvement in forecast accuracy across all forecasting rounds is about 10 to 20 percentage points. Even the simplest combination method, the arithmetic average on all retained models, produces consistently smaller forecast errors than the univariate benchmark forecast. By employing the in-sample information, Bayesian weights performance similar to the equal weighting scheme.²⁷ The optimized weights based on in-sample performance show quite heterogeneous results. Granger-Ramanathan weights as well as the shrunk weights performed poorly at the early forecast stages. Later, when more information is available, they show quite satisfactory results.²⁸ MMA weights also shares the sensitivity of the other two optimized weights. It performs relatively well for the first forecast rounds (F1-F2) and again at the later steps (F7-F9). Therefore, we can conclude that the in-sample information of the different models for computing the weighting schemes does not always help to improve the forecasting accuracy. In particular, optimized weights tend to be better when the information on the current quarter increase, otherwise they can be unreliable. This is also reflected in the extreme case where only the best fitting model is used (minSIC).

Table 1: Forecasting performance for direct GDP based on forecast combination

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|----------|---------|--------|--------|--------|--------|--------|--------|--------|--------|
| AR | 1.090 | 1.090 | 1.090 | 1.090 | 1.080 | 1.080 | 1.080 | 1.080 | 1.080 |
| mean | 0.948 | 0.928 | 0.909 | 0.860* | 0.868 | 0.854 | 0.851 | 0.824 | 0.825 |
| min SIC | 1.713 | 1.714 | 1.464 | 0.901 | 0.761 | 0.858 | 0.842 | 0.811 | 0.802 |
| bayesian | 0.947 | 0.928 | 0.908 | 0.860* | 0.867 | 0.852 | 0.848 | 0.820 | 0.821 |
| gr | 1.352 | 1.168 | 1.172 | 1.025 | 1.059 | 1.007 | 0.957 | 0.785 | 0.755 |
| shrink | 1.324 | 0.810 | 0.950 | 0.771 | 1.089 | 0.995 | 0.943 | 0.739 | 0.715 |
| MMA | 0.901** | 0.905* | 1.433 | 1.442 | 1.036 | 0.967 | 0.901 | 0.757 | 0.707* |
| msfe | 0.888 | 0.874 | 0.863* | 0.806* | 0.808 | 0.783 | 0.776 | 0.730* | 0.731* |
| rank | 0.679* | 0.675* | 0.704* | 0.650* | 0.618* | 0.615* | 0.592* | 0.553* | 0.556* |
| egr | 2.157 | 2.051 | 1.032 | 0.886 | 0.850 | 0.836 | 0.838 | 0.659 | 0.644 |

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

Turning to weighting schemes based on the models past out-of-sample performance, we find that they result in a large improvement in forecast accuracy (up to 45%). In particular msfe weights

²⁷ The unit information prior implies that the Bayesian weights deviate only by a small amount from the equal weighting scheme. Choosing a different prior which puts more weight to the in-sample performance does not result in a much better out-of-sample performance and was found to be less reliable across all different forecasting rounds and GDP components.

²⁸ One reason for the heterogeneous performance of the optimized weights may be the fact that based on these criteria only a small number of all possible models gets a weight different from zero. This results in a forecasting behavior which is less stable compared to modelling schemes that use more available information. This also explains why the shrinkage procedure is often found to be superior to the pure GR weights, since it puts less weight to just a small number of models.

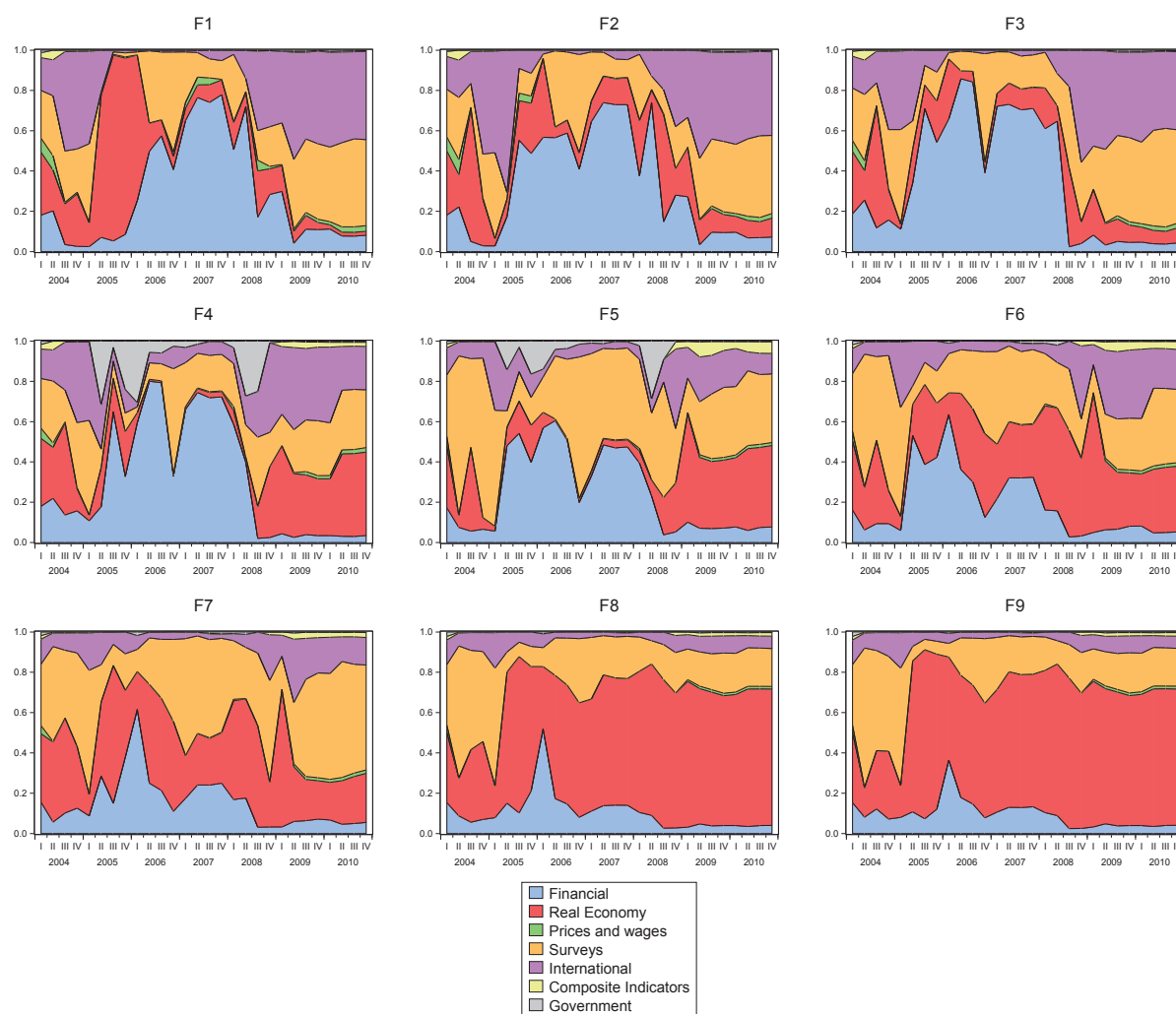
and rank-based weights consistently outperformed the benchmark model. This is consistent with the findings of Drechsel and Scheufele (2012b), who also obtain the best forecasting results based on msfe weights for industrial production in Germany. However they do not consider rank-based weights that show by far the smallest forecast errors in our settings and are significantly better than the AR model. The performance of optimized weights based on the model’s out-of-sample information depends - comparable to the corresponding in-sample weights - on the state of information. For the later forecast rounds the forecast errors are even smaller than the pure variance-based msfe weights.

Our results based on forecasting the GDP growth directly by means of pooling MIDAS and ARDL models confirm that forecast combination may result in large improvements in forecast (and nowcast) accuracy (Stock and Watson, 2004; Timmermann, 2006). In particular we can support the findings of Kuzin *et al.* (2009) that pooling becomes even more important under mixed data frequencies. Rank-based weights offer consistent smaller forecast errors than any other (and more complicated) procedure. This may be due to the fact, that ranks are less sensitive to outliers than weights directly based on the average squared forecast errors (Timmermann, 2006). One advantage of model averaging compared to procedures that combine the information before estimation (e.g. dynamic factor models) is that the weights directly reflect the influence of each model for the averaged forecast. This offers the opportunity to see which kind of information is used to construct the forecast and may be helpful in interpreting the results (see, Giannone *et al.*, 2008, in the case of factor models). Figure 3 shows the time varying weights assigned to each variable block (financial data, surveys, real economy, international indicators,...) for each of the nine forecasting rounds. As can be seen for each of the different forecasting rounds, time variation plays an important role, although it tends to be more important for the first forecasting rounds (where the signals are generally noisier). The need for time variation also may explain why rank-based weights outperform the equal weighting scheme or in-sample weights which adapt changes later than weights based on out-of-sample performance. Further, we can confirm the findings of Banbura and Rünstler (2011) and Drechsel and Maurin (2011) that “hard data” (industrial production, turnovers,...) is more and more important as additional information of this series gets available, while at the first forecasting rounds surveys and financial data contribute at most to the forecast.

4.2 Forecasting the GDP components

If one turns to the mixed frequency approach for the disaggregates we find many similarities to the direct GDP forecasts although it is also evident that the information employed by coincident and leading indicators help to forecast some components better than others (see Tables 7 and 8 in the appendix). First, as with the direct GDP forecast, we find for the GDP components that the forecasting accuracy generally improves over the forecast rounds. Second, rank-based weights perform best through basically all subcomponents and for all forecasting rounds. Third,

Figure 3: Weights allocated to each block (Rank-based scheme)



Note: Time varying weights allocated to different indicator blocks are shown for bi-weekly forecast rounds (F1-F9).

optimized weights show again heterogeneous results. In some cases optimized weights based on in-sample information perform among the best averaging schemes and provide large and significant improvements relative to the benchmark models (e.g. construction, producing sector, construction investment,...). In other situations these weights are unreliable and perform even worse than the benchmark (e.g. private consumptions, services,...). Fourth, model selection should be circumvented (minSIC mostly does not result in significant improvements), although there exist some few exceptions (e.g. for exports, construction investment). The equal weighting scheme and Bayesian weights show stable behavior in the sense that in most cases they yield smaller forecast errors than the univariate benchmark forecast and only in few cases errors that are slightly higher than the AR model.

More specifically for the demand side, we find that exports, imports and building investment are the GDP components that can be well forecasted using the information of leading indicators. Compared to the benchmark, the forecast error can be decreased considerably by model averaging, e.g. up to 50% for exports. For private consumption, which has by far the largest expenditure share, government consumption and remaining gross fixed investment only some model averaging schemes (msfe and rank) turn out to be helpful. Improvement gains for those variables remain modest. Due to consumption smoothing the benchmark forecast error for private consumption (which is a random walk with drift in most cases) is relatively small compared to other components which makes it hard to forecast it. The benchmark AR-forecast for inventories cannot be outperformed by none of the averaging criteria up to forecast round F5. After the lagged depended variable was released this result changes dramatically.

The situation for the production side is similar. We find that the sectors of construction, manufacturing and wholesale, retail trade and transport can be reproduced very well. This is not surprising since many of the indicators are more or less connected with these sectors. Improvements of leading indicator forecasts for this sector are substantial and highly significant. Model averaging entails substantial gains to the AR-forecast among 30-40%. For the sectors financing, renting and corporate services, and public and private services some signals from leading indicators are sent but only few model averaging schemes turn out to be better than the benchmark model. Again rank and msfe are the dominant weighting schemes. However, the gains compared to the benchmark AR-forecast are less than 20%. Even taxes minus subsidies provide few significantly better results after the fourth forecast round (due to the knowledge of monthly tax revenue indicators). Only agriculture is the sector where none of the averaging schemes provide significantly better results.

4.3 Comparing the direct forecast with disaggregate approaches

While we found that most GDP subcomponents can be forecasted well by our proposed procedure, we investigate how the disaggregate procedures perform relative to the direct method. Table 2 shows pairwise comparisons of the three different forecasting procedures for different combination schemes and for all forecasting rounds. For instance, using the equal weighting scheme (mean), our results show that at the first forecasting round (F1) demand-side aggregation yields slightly better results (indicated by a value less than one) compared to the direct approach. But the result based on production-side aggregation does not beat the direct forecast. However, both results are not statistically significant. In general, for the equal weighting scheme and the Bayesian weights we find that all three procedures produce quite similar results (the relative performance deviates not more than 10% from each other). Neither procedure dominates the other significantly. For the optimized weights (gr, shrink and MMA) we find that the production-side approach produces on average smaller errors than the demand-side approach. In some cases (e.g. for forecasting rounds after F5) forecast errors are about 50% smaller (and in

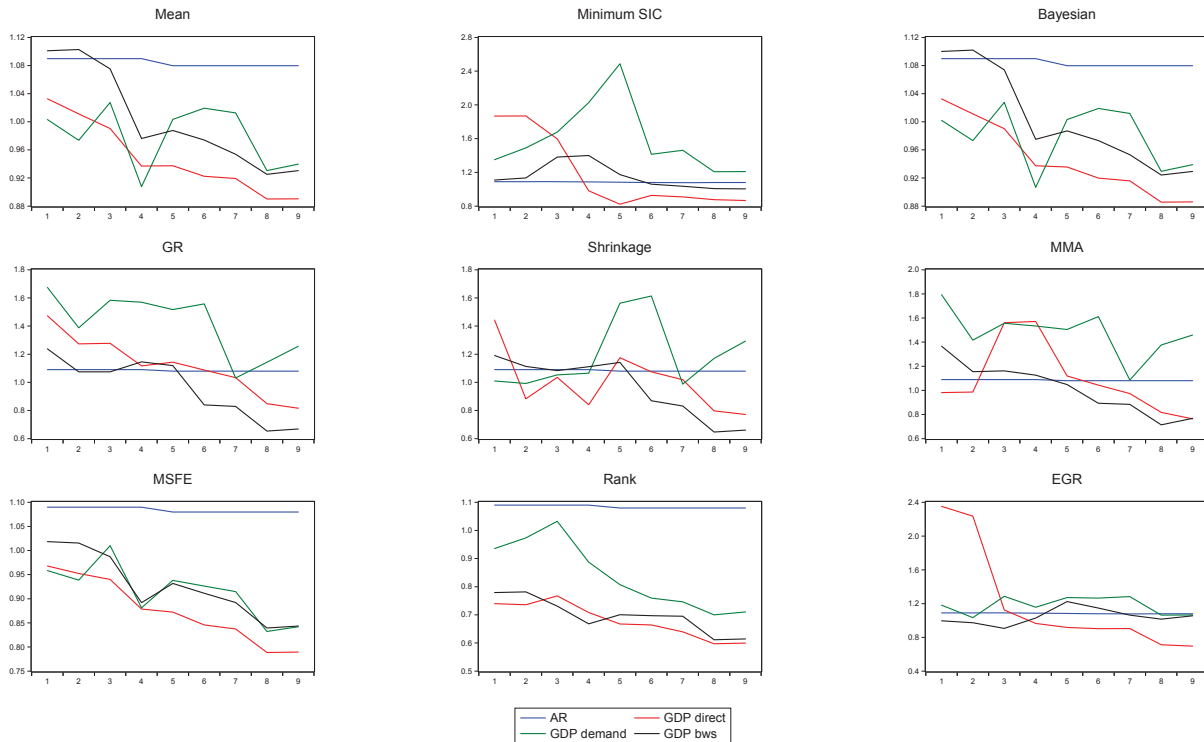
Table 2: Comparison of GDP forecasts based on different methods (direct and bottom-up)

| | 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 | |
| mean | | | | | | | | | | | | | | | | | | | |
| demand | 0.971 | 0.963 | 1.037 | 0.969 | 1.070 | 0.969 | 1.105 | 1.102 | 1.105 | 1.045 | 1.056 | 1.092 | 1.045 | 1.056 | 1.045 | 1.056 | 1.045 | 1.056 | 1.056 |
| gva | 1.066 | 1.091 | 1.133 | 1.047 | 1.054 | 1.076 | 1.056 | 1.038 | 1.054 | 1.040 | 0.956 | 1.038 | 0.942 | 1.045 | 0.994 | 1.045 | 0.994 | 1.045 | 0.990 |
| minSIC | | | | | | | | | | | | | | | | | | | |
| demand | 0.724 | 0.798 | 1.051 | 2.065* | 3.027 | 2.065* | 1.526* | 1.608* | 1.526* | 1.379 | 1.526* | 1.608* | 1.379 | 1.396 | 1.379 | 1.396 | 1.379 | 1.396 | 1.396 |
| gva | 0.594 | 0.607 | 0.761 | 1.427 | 1.428 | 0.691 | 1.145 | 1.138 | 1.428 | 0.708 | 1.145 | 1.138 | 0.708 | 1.150 | 0.834 | 1.150 | 0.834 | 1.160 | 0.831 |
| bayesian | | | | | | | | | | | | | | | | | | | |
| demand | 0.971 | 0.963 | 1.038 | 0.967 | 1.072 | 0.967 | 1.108 | 1.105 | 1.072 | 1.050 | 1.108 | 1.105 | 1.050 | 1.060 | 1.050 | 1.060 | 1.049 | 0.990 | 0.990 |
| gva | 1.065 | 1.090 | 1.132 | 1.040 | 1.055 | 1.076 | 1.058 | 0.955 | 1.055 | 0.984 | 1.058 | 0.955 | 1.044 | 0.994 | 1.044 | 0.994 | 1.049 | 0.990 | 0.990 |
| gr | | | | | | | | | | | | | | | | | | | |
| demand | 1.137** | 1.090* | 1.239 | 1.406 | 1.327* | 1.406 | 1.433 | 0.998 | 1.327* | 1.347 | 1.433 | 0.998 | 1.347 | 1.541 | 1.347 | 1.541 | 1.347 | 1.541 | 1.541 |
| gva | 0.840 | 0.739 | 0.841 | 1.026 | 0.978 | 0.730 | 0.772 | 0.539 | 0.978 | 0.804 | 0.772 | 0.539 | 0.804 | 0.820 | 0.771 | 0.572 | 0.820 | 0.532 | 0.532 |
| shrink | | | | | | | | | | | | | | | | | | | |
| demand | 0.700 | 1.123 | 1.017 | 1.267** | 1.330 | 1.267** | 1.502 | 0.969 | 1.330 | 1.467 | 1.502 | 0.969 | 1.467 | 1.675 | 1.467 | 1.675 | 1.467 | 1.675 | 1.675 |
| gva | 0.825 | 1.179 | 1.047 | 1.321 | 0.971 | 1.043 | 0.809*0.539* | 0.817 | 0.971 | 0.843 | 0.809*0.539* | 0.817 | 0.843 | 0.856 | 0.811*0.553* | 0.856 | 0.511 | 0.511 | 0.511 |
| MMA | | | | | | | | | | | | | | | | | | | |
| demand | 0.954 | 1.005 | 1.180 | 1.063 | 1.314 | 1.063 | 1.430 | 1.029 | 1.314 | 1.380 | 1.430 | 1.029 | 1.380 | 1.554 | 1.380 | 1.554 | 1.380 | 1.554 | 1.554 |
| gva | 0.855 | 0.896 | 0.813 | 0.928 | 1.010 | 0.873 | 0.762*0.533* | 0.785 | 1.010 | 0.763 | 0.762*0.533* | 0.785 | 0.763 | 0.816 | 0.784 | 0.568 | 0.816 | 0.526 | 0.526 |
| MFSE | | | | | | | | | | | | | | | | | | | |
| demand | 0.990 | 0.986 | 1.075 | 1.003 | 1.076 | 1.003 | 1.095 | 1.092 | 1.076 | 1.055 | 1.095 | 1.092 | 1.055 | 1.067 | 1.055 | 1.067 | 1.068 | 1.002 | 1.002 |
| gva | 1.052 | 1.063 | 1.050 | 1.015 | 1.068 | 0.993 | 1.078 | 0.984 | 1.068 | 0.975 | 1.078 | 0.984 | 1.064 | 1.068 | 1.009 | 1.068 | 1.002 | 1.002 | 1.002 |
| rank | | | | | | | | | | | | | | | | | | | |
| demand | 1.265* | 1.323* | 1.345* | 1.252 | 1.209 | 1.252 | 1.144 | 1.167 | 1.209 | 1.172 | 1.144 | 1.167 | 1.172 | 1.184 | 1.172 | 1.184 | 1.024 | 0.865 | 0.865 |
| gva | 1.053 | 0.833 | 1.062 | 0.943* | 1.050 | 0.753* | 1.050 | 0.918 | 1.050 | 0.868 | 1.050 | 0.918 | 1.087 | 1.024 | 0.874 | 1.024 | 0.865 | 0.865 | 0.865 |
| egr | | | | | | | | | | | | | | | | | | | |
| demand | 0.502 | 0.462 | 1.143 | 1.198 | 1.386* | 1.198 | 1.401* | 1.418 | 1.386* | 1.493* | 1.401* | 1.418 | 1.418 | 1.530* | 1.493* | 1.530* | 1.418 | 1.530* | 1.530* |
| gva | 0.423 | 0.843 | 0.806**0.705** | 1.065 | 1.333 | 0.889 | 1.272 | 0.908 | 1.333 | 0.962 | 1.272 | 0.908 | 1.174 | 1.427 | 0.956 | 1.427 | 0.956 | 1.517 | 0.991 |

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 number reflects the relative forecast error, whereas the numerator is given by the row and the denominator by the column, respectively.

some cases statistically significant) for the production side compared to the other disaggregate approach. Also with respect to the direct approach, the supply side provides some improvements (up 20%) by using in-sample optimized weights. Similar to equal weights and Bayesian weights, the msfe weighting scheme does not show much variation between the three forecasting methods. For this setting the direct approach turns out to be quite successful. Rank-based weights which dominate all other weighting schemes for all subcomponents report that the direct approach clearly dominates (sometimes significantly) the demand-side approach. Also with respect to the supply-side approach, the direct approach is hard to beat. Only for F3 and F4 the supply-side methods significantly outperforms the direct approach.

Figure 4: RMSFE over forecast rounds



Note: RMSFEs for direct and bottom-up forecasts are shown together with the RMSFE of the AR-forecast for several weighting schemes and different forecasting rounds (F1-F9).

Figure 4 plots the RMSFE for the three forecasting methods along with the RMSFE of the univariate direct AR forecast depending on the forecast combination schemes and for different forecasting rounds. This makes it also possible to compare the performance across different pooling techniques. As expected, the rank-based scheme shows the best forecasting performance (mostly based on the direct approach). Also for msfe weights, the direct approach is more promising. The supply-side approach based on optimized weights produces also good results for F6-F9. In particular, the gr and shrink weighting schemes are relatively precise in situations where most of the information is available. In this situation (and for these weighting schemes) the production-side approach is superior (black line). However, due to the fact that the rank-

Table 3: Forecast encompassing tests

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|----------|------|------|------|------|------|------|------|------|------|
| mean | 0.00 | 0.03 | 0.01 | 0.36 | 0.60 | 0.81 | 0.70 | 0.51 | 0.56 |
| min SIC | 0.00 | 0.00 | 0.00 | 0.68 | 0.25 | 0.04 | 0.01 | 0.00 | 0.00 |
| bayesian | 0.00 | 0.02 | 0.01 | 0.40 | 0.60 | 0.82 | 0.74 | 0.53 | 0.58 |
| gr | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| shrink | 0.00 | 0.44 | 0.49 | 0.14 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| MMA | 0.90 | 0.91 | 0.00 | 0.00 | 0.01 | 0.00 | 0.03 | 0.00 | 0.03 |
| msfe | 0.25 | 0.17 | 0.00 | 0.88 | 0.60 | 0.69 | 0.61 | 0.52 | 0.57 |
| rank | 0.86 | 0.13 | 0.00 | 0.00 | 0.81 | 0.55 | 0.80 | 0.28 | 0.36 |
| egr | 0.00 | 0.00 | 0.00 | 0.36 | 0.05 | 0.01 | 0.04 | 0.01 | 0.00 |

Note: The p-values of the Wald-Test are shown. The reference model is given by the direct model and is tested against the demand and supply-sided approach.

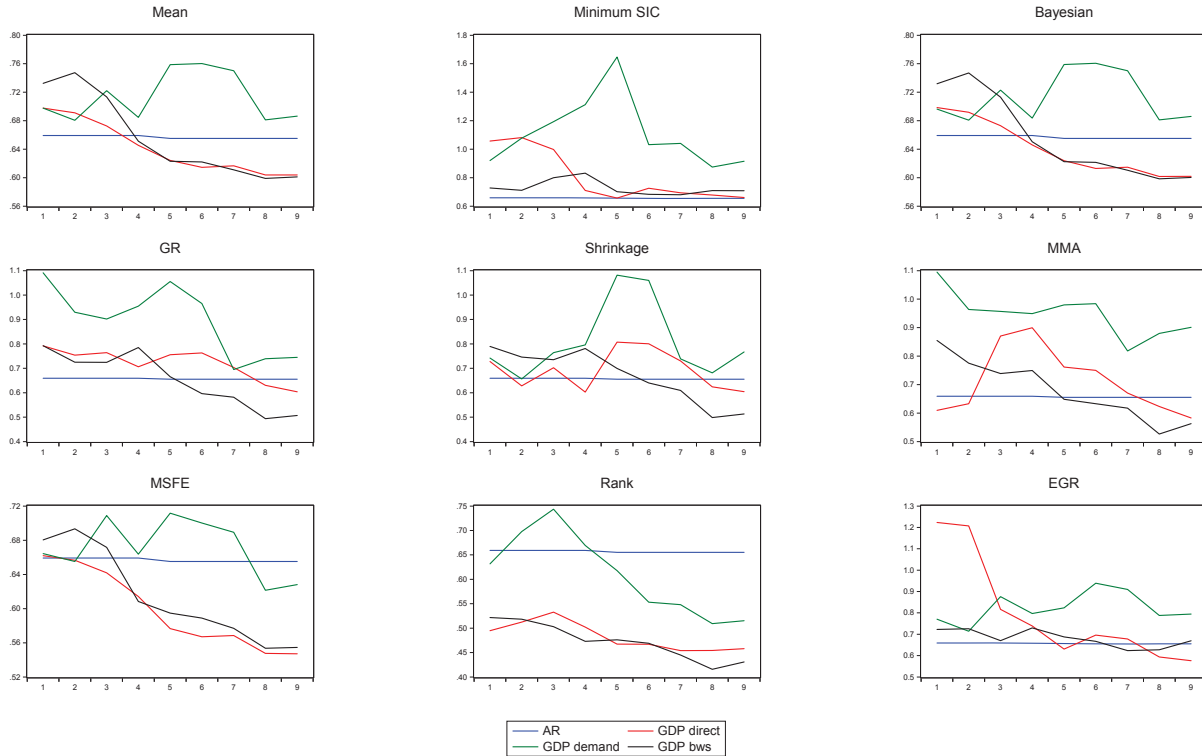
based weights outperform the optimized weights for all horizons, the direct approach always dominates.

While we have examined the different forecasting methods and averaging schemes in terms of average forecasting performance, this does not imply that any method is conditionally efficient (see section 3.4). Therefore, Table 3 reports the encompassing tests to investigate whether there is still information contained in the disaggregated approaches beyond that in the direct approach. The test reveals that the dominating direct rank-based averaging scheme does encompass the demand- and production-sided approach in most of the time. Only for two out of nine forecasting rounds there is some room for improvements. This is also reflected in Table 2 where the production-side approach is significantly better than the direct approach. Similar results can be found for msfe (which encompasses the bottom-up approaches for eight out of nine forecasting rounds), the equal-weighting scheme and the Bayesian weights. The two later procedures are superior from forecast round F4 onwards. For optimized weights we find that in most situations the direct approach does not encompass the bottom-up approaches. Under optimized in-sample weights the bottom-up approaches do provide some information not included in the direct approach. However, by comparing the resulting forecasting performance across different pooling techniques we can conclude that the direct approach is hard to beat by disaggregation of GDP (at least when using the most successful model averaging scheme).

5 Robustness Analysis

To check the robustness of our results with respect to the specified loss function and with respect to stability issues, we undertake some additional calculations. Instead of assuming quadratic loss, one can also look at absolute loss. In practice, the implications of the two loss functions coincide to a greater or lesser extent. The only difference is that outliers are weighted more heavily under squared loss. Figure 5 presents the mean absolute forecast errors (MAFEs) for the three different forecasting methods (direct, demand side, production side) and the AR-benchmark forecast which can be directly compared with Figure 4. Since our proposed forecasting methods

Figure 5: MAFE over forecast rounds



Note: MAFEs for direct and bottom-up forecasts are shown together with the RMSFE of the AR-forecast for several weighting schemes and different forecasting rounds (F1-F9).

include model specification, selection and combination which are all based on quadratic objective criteria we would expect that our methods perform better under squared loss than under absolute loss. Indeed, the two figures imply that the forecast methods perform relatively better in terms of RMSFEs (relative to the benchmark model). Nevertheless, the general tendency of both loss-function measures are similar. Again, rank-based weights produce the lowest forecast errors and direct as well as the production-sided approach perform equally well (within this category). However, it is evident that for absolute loss the bottom-up approach improves slightly relative to the remaining methods whereas the demand-sided approach is clearly inferior (for all averaging schemes under investigation). Thus, under absolute loss the bottom-up approach, namely from the production side, produces equal or even slightly lower forecast errors compared to the two remaining methods; although the differences to the direct approach remain small.

Another issue concerns the stability throughout the out-of-sample period. Drechsel and Scheufele (2012a) and Drechsel and Scheufele (2012b) show for Germany that the performance of leading indicator models changes dramatically during the period 2008q1-2009q2. Interestingly, output volatility in Germany has increased considerably since the outbreak of the financial crisis in 2008. After the slump in production, we saw a fast catching-up process with high GDP growth. Therefore, we would like to investigate the performance of our forecasting and nowcasting pro-

cedure within this subperiod (which we term crisis period and which is basically defined from the outbreak of the crisis in 2008q1 to the final observation 2010q4). Additionally, we can observe whether the relative performance of the direct approach compared to the disaggregated methods remains stable. Using several weighting schemes Table 4 compares the three methods relative to the direct AR benchmark forecast. Due to the volatility of GDP within this subperiod the average RMSFE for the univariate model is about one third higher relative to the full sample. The relative performance of the modelling schemes improved slightly in this period which reflects Drechsel and Scheufele’s (2012b) result that the performance of leading indicator models and corresponding combination schemes improved relative to univariate models within the crisis. Except for forecasting rounds F3 and F4, the direct forecast based on the ranking scheme does best in terms of RMSFEs. Also optimized weights, i.e. gr and shrink, do remarkably well at the last forecasting round when it comes to the production-sided approach. For the demand side, none of the weighting schemes applied provide significantly better results relative to the AR forecast. Therefore, we can summarize that our general results remain relatively robust within this subperiod. Another issue concerns the stability throughout the out-of-sample period.

Table 4: Forecasting performance during the crisis period

| | F=1 | F=2 | F=3 | F=4 | F=5 | F=6 | F=7 | F=8 | F=9 |
|-------------------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| AR | 1.578 | 1.578 | 1.578 | 1.578 | 1.563 | 1.563 | 1.563 | 1.563 | 1.563 |
| <i>direct GDP forecast</i> | | | | | | | | | |
| mean | 0.951 | 0.929 | 0.910 | 0.852 | 0.863 | 0.851 | 0.850 | 0.821 | 0.821 |
| min SIC | 1.753 | 1.750 | 1.470 | 0.823* | 0.675 | 0.794 | 0.812 | 0.773 | 0.762 |
| bayesian | 0.950 | 0.929 | 0.910 | 0.852 | 0.862 | 0.849 | 0.846 | 0.816 | 0.816 |
| gr | 1.402 | 1.205 | 1.201 | 1.033 | 1.065 | 1.008 | 0.958 | 0.765 | 0.730 |
| shrink | 1.368 | 0.805 | 0.942 | 0.742 | 1.082 | 0.966 | 0.925 | 0.691 | 0.663 |
| MMA | 0.913* | 0.917 | 1.482 | 1.487 | 1.042 | 0.967 | 0.901 | 0.746 | 0.689 |
| msfe | 0.891 | 0.875 | 0.865 | 0.798* | 0.805 | 0.781 | 0.775 | 0.725* | 0.725* |
| rank | 0.681* | 0.670* | 0.704* | 0.643* | 0.607* | 0.611* | 0.586* | 0.545* | 0.545* |
| egr | 2.247 | 2.132 | 1.015 | 0.849 | 0.826 | 0.806 | 0.815 | 0.594 | 0.588 |
| <i>demand-side GDP forecast</i> | | | | | | | | | |
| mean | 0.914 | 0.901 | 0.948 | 0.825 | 0.875 | 0.896 | 0.892 | 0.812 | 0.822 |
| min SIC | 1.203 | 1.321 | 1.506 | 1.896 | 2.370 | 1.248 | 1.268 | 0.773 | 0.803 |
| bayesian | 0.913 | 0.901 | 0.948 | 0.824 | 0.875 | 0.896 | 0.891 | 0.811 | 0.821 |
| gr | 1.546 | 1.272 | 1.484 | 1.472 | 1.402 | 1.451 | 0.935 | 1.022 | 1.153 |
| shrink | 0.913 | 0.908 | 0.951 | 0.954 | 1.439 | 1.501 | 0.884 | 1.047 | 1.180 |
| MMA | 1.673 | 1.303 | 1.444 | 1.418 | 1.412 | 1.518 | 0.965 | 1.256 | 1.348 |
| msfe | 0.876 | 0.868 | 0.930 | 0.803 | 0.818 | 0.811 | 0.800 | 0.725 | 0.735 |
| rank | 0.852 | 0.900 | 0.946 | 0.815 | 0.697 | 0.656 | 0.641 | 0.600 | 0.611 |
| egr | 1.09 | 0.96 | 1.182 | 1.048 | 1.073 | 1.085 | 1.116 | 0.861 | 0.866 |
| <i>production-side GDP forecast</i> | | | | | | | | | |
| mean | 1.016 | 1.018 | 0.990 | 0.890 | 0.908 | 0.895 | 0.880 | 0.852 | 0.855 |
| min SIC | 1.007 | 1.026 | 1.289 | 1.310 | 1.063 | 0.943 | 0.935 | 0.906 | 0.903 |
| bayesian | 1.016 | 1.017 | 0.988 | 0.889 | 0.908 | 0.895 | 0.879 | 0.851 | 0.854 |
| gr | 1.161 | 0.995 | 0.994 | 1.058 | 1.044 | 0.754 | 0.751 | 0.567* | 0.579* |
| shrink | 1.106 | 1.030 | 0.997 | 1.016 | 1.068 | 0.778 | 0.754 | 0.564* | 0.572* |
| MMA | 1.283 | 1.068 | 1.082 | 1.044 | 0.981 | 0.820 | 0.811 | 0.626* | 0.684* |
| msfe | 0.938 | 0.935 | 0.906 | 0.810* | 0.854 | 0.835 | 0.821 | 0.769 | 0.771 |
| rank | 0.722* | 0.727* | 0.670* | 0.606* | 0.641* | 0.637* | 0.646* | 0.565* | 0.560* |
| egr | 0.909 | 0.876 | 0.809 | 0.932 | 1.145 | 1.065 | 0.994 | 0.950 | 0.981 |

Note: Relative RMSFE based on various weighting schemes are shown for the 9 forecast rounds over the crisis period for direct GDP forecast and bottom-up GDP forecasts (relative to the RMSFE of the AR forecast given in the first line and shaded in grey).

6 Conclusion

In this paper we presented a complete methodology to obtain early GDP estimates using a large set of information. Therefore, we employ MIDAS models to bridge the gap between monthly indicators and quarterly GDP. Additionally, we make extensive use of model averaging schemes to combine a variety of leading indicators forecasts. We do explicitly take into account the publication lags of available data by employing bi-weekly forecasting rounds.

Besides presenting a framework for now- and forecasting GDP, our main contribution is to compare direct with bottom-up approaches for short-term GDP predictions. It is thus a test whether contemporaneous aggregation does lead to smaller forecast errors. In the context of leading and coincident indicator models we find only limited evidence that disaggregation leads to a better predictive ability. Therefore this study reveals important implications for practitioners in central banks or other institutions which have to rely on early information to judge the consequences for economic activity. Given the additional effort due to specifying models for the subcomponents, we can suggest to apply the direct forecast for early GDP estimates. Among the two disaggregated procedures, the supply-sided approach where GDP is divided into its different formation sectors clearly outperforms the demand-sided (or expenditure) approach and performs similar to the direct approach. In some cases the supply-sided approach even does slightly better than the direct approach. This holds, at least, in situations of short-term forecasts, when dealing with a huge amount of available information. In the case of structural models or/and for longer forecasting horizons one may get different results.

To consider a realistic nowcast set up, we presented a complete methodology to obtain early GDP estimates using a large set of information. Therefore, we employ MIDAS models to bridge the gap between monthly indicators and quarterly GDP. Additionally, we make extensive use of model averaging schemes, to combine a variety of leading indicators forecasts. We do explicitly take into account the publication lags of available data by employing bi-weekly forecasting rounds. As a by-product, we found that combination weights based on ranks computed from the models past performance do very well in nowcasting German GDP growth. The proposed approach with MIDAS models and forecast pooling marks an alternative to the framework presented by Banbura *et al.* (2011) and Angelini *et al.* (2011). Our method can be easily applied, since it consists of linear estimated single equations which are combined by simple weights to form an aggregate GDP prediction that fulfils certain optimality conditions: the forecast errors decrease as more information becomes available, it does significantly outperform the univariate benchmark and it can hardly be improved by disaggregation. One subject for future research would therefore be the comparison of the methods as proposed in this paper with those that use factor and state-space models to deal with standard nowcasting procedures.

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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 | capital investments | | q |
| IVOR | inventories | | q |
| GVAFFFD | 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 | 3.5 | q |
| PQ3013A | mortgage loans | 3.5 | q |
| PQ3001A | lending to enterprises & self employed | 3.5 | q |
| PQ3020A | lending to manufacturing industry | 3.5 | q |
| PQ3022A | lending to construction industry | 3.5 | q |
| PQ3023A | lending to wholesale & retail trade & repair industry | 3.5 | q |
| PQ3185A | lending to service sector: housing enterprises | 3.5 | q |
| PQ3189A | lending to service sector: holding companies | 3.5 | q |
| PQA350A | bank lending to dom.enterprises & individuals: all banks | 3.5 | q |
| PQ3151A | housing loans - dom.entps. | | |
| | hh, total, all banks | 3.5 | q |
| SU0101R | day-to-day-money market rate (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 yrs | 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 listed federal bonds outstanding maturity 3-5 yrs avg. rate | 0 | m |
| WU9553R | yields on listed federal bonds outstanding 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 incl.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 enterprises& 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) | 4 | q |
| IPTOT | IP including construction | 1.5 | m |
| IPMAN | industrial production: manufacturing | 1.5 | m |

To be continued...

| Label | Name | Months of Publication Lags | Frequency |
|----------|---|----------------------------|-----------|
| 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 |
| 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 |
| STFEEXEG | 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.construction 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-incl. cnstr. | 2 | m |

To be continued...

| Label | Name | Months of Publication Lags | Frequency |
|--------------------------|---|----------------------------|-----------|
| WGUS01LAB | bdg.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 |
| 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.sector | 1.5 | m |
| ESEIHTT | 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 | 0.5 | q |
| WDIFEXPER | Economic expectations - world | 0.5 | q |
| IFDMT | mfg.: capacity utilization | 0.5 | q |
| ZEWST | ZEW present economic situation | 0 | m |
| ZEWECRSR | 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: mfg. - consumer goods | 0 | m |
| IFOMCKQ | business expectations: mfg. - 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 |
| IFOBDOQ | business climate index: construction | 0 | m |
| IFOBDOQ | business expectations: construction | 0 | m |
| IFDCTIQ | cnstr.ind.: assessment of orders on hand | 0 | m |
| IFPCTWQ | cnstr.ind.: unfavourable weather 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.with regard 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 | retail sale - assessment of inventories | 0 | m |

To be continued...

| Label | Name | Months of Publication Lags | Frequency |
|---------------------------------|--|----------------------------|-----------|
| IFRSAHQ | retail 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 |
| 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 finished goods | 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 | construction confidence indicator | 0 | m |
| EUSESIG | economic sentiment indicator | 0 | m |
| PMIBD | PMI manufacturing | 0 | m |
| PMIBDS | PMI services | 0 | m |
| PMIEUR | PMI composite euro area | 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 (normalized) | 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 (normalized) | 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 (normalized) | 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 (normalized) | 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 (normalized) | 1.5 | m |
| Government | | | |
| BU2064A | tax revenue - EU customs duties | 1.5 | m |
| BU2009A | tax revenue - income taxes, total | 1.5 | m |

To be continued...

| Label | Name | Months of Publication Lags | Frequency |
|---------|---------------------------------------|----------------------------|-----------|
| 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 4 months. 0 indicates that the indicator is instantaneously available at the end of the month. For quarterly indicators, the publication lag is measured as monthly interval relative to the first month of the respective quarter.

Table 6: Number of Indicators Used

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|--|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| GDP | 65 | 66 | 70 | 80 | 97 | 107 | 114 | 123 | 123 |
| consumer expenditure | 23 | 23 | 26 | 25 | 27 | 29 | 29 | 30 | 30 |
| exports of goods & services | 85 | 89 | 94 | 106 | 124 | 125 | 127 | 128 | 128 |
| imports of goods & services | 102 | 103 | 104 | 115 | 125 | 128 | 131 | 134 | 132 |
| government consumption | 14 | 15 | 15 | 15 | 21 | 24 | 26 | 25 | 24 |
| construction investment | 23 | 21 | 21 | 22 | 32 | 37 | 39 | 39 | 38 |
| remaining gross fixed investment | 224 | 225 | 226 | 229 | 199 | 202 | 204 | 203 | 203 |
| inventories | 7 | 7 | 6 | 5 | 205 | 208 | 208 | 206 | 206 |
| agriculture, forestry & fishing | 9 | 9 | 9 | 12 | 12 | 11 | 11 | 9 | 8 |
| construction | 20 | 18 | 19 | 21 | 82 | 84 | 87 | 88 | 87 |
| financing,renting & corporate services | 143 | 146 | 148 | 157 | 174 | 187 | 188 | 193 | 192 |
| producing sector excl. construction | 29 | 33 | 36 | 39 | 132 | 135 | 142 | 153 | 152 |
| public & private service suppliers | 11 | 9 | 8 | 8 | 72 | 70 | 74 | 72 | 70 |

Note: For each forecast round (1-9) the average number of indicators that is used to generate the individual GDP aggregate forecasts is given.

Table 7: GDP bottom-up forecast - demand approach

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|--|---------|---------|---------|---------|----------|----------|----------|----------|----------|
| consumer expenditure | | | | | | | | | |
| AR | 0.710 | 0.710 | 0.710 | 0.710 | 0.715 | 0.715 | 0.715 | 0.715 | 0.715 |
| mean | 1.065 | 1.054 | 1.086 | 1.052 | 1.062 | 1.034 | 1.036 | 0.960 | 0.964 |
| min SIC | 1.388 | 1.213 | 1.336 | 1.206 | 1.274 | 1.342 | 1.373 | 1.531 | 1.531 |
| bayesian | 1.066 | 1.056 | 1.087 | 1.052 | 1.062 | 1.036 | 1.038 | 0.962 | 0.965 |
| gr | 1.093 | 1.087 | 1.125 | 1.067 | 1.036 | 1.093 | 1.081 | 1.073 | 1.072 |
| shrink | 1.094 | 1.130 | 1.174 | 1.121 | 1.278 | 1.332 | 1.234 | 1.274 | 1.274 |
| MMA | 1.271 | 1.129 | 1.217 | 1.148 | 1.160 | 1.169 | 1.202 | 1.214 | 1.224 |
| msfe | 1.018 | 1.023 | 1.064 | 1.032 | 1.027 | 0.991 | 0.994 | 0.908* | 0.912* |
| rank | 0.850** | 0.913* | 0.962 | 0.879* | 0.883** | 0.802** | 0.811*** | 0.742*** | 0.743*** |
| egr | 1.368 | 1.080 | 1.163 | 1.098 | 1.084 | 1.143 | 1.184 | 1.096 | 1.096 |
| exports of goods & services | | | | | | | | | |
| AR | 3.650 | 3.650 | 3.650 | 3.650 | 3.611 | 3.611 | 3.611 | 3.611 | 3.611 |
| mean | 0.832* | 0.807* | 0.803* | 0.744* | 0.725* | 0.706* | 0.701* | 0.679* | 0.681* |
| min SIC | 0.868 | 0.866 | 0.910 | 1.144 | 1.396 | 0.832 | 0.837 | 0.603* | 0.603* |
| bayesian | 0.832* | 0.807* | 0.803* | 0.744* | 0.725* | 0.706* | 0.701* | 0.678* | 0.681* |
| gr | 1.042 | 0.898 | 0.975 | 0.953 | 0.926 | 0.863 | 0.690* | 0.768 | 0.778 |
| shrink | 0.881** | 0.855* | 0.838* | 0.804* | 0.958 | 0.980 | 0.745* | 0.793 | 0.810 |
| MMA | 1.026 | 0.885 | 0.964 | 0.895 | 0.871 | 0.971 | 0.747 | 0.923 | 0.933 |
| msfe | 0.805* | 0.777* | 0.775* | 0.706* | 0.689* | 0.662* | 0.654* | 0.624* | 0.626* |
| rank | 0.695** | 0.661* | 0.667* | 0.606* | 0.565* | 0.529* | 0.522* | 0.493* | 0.494* |
| egr | 0.969 | 0.938 | 0.896 | 0.910 | 0.746 | 0.705 * | 0.692 * | 0.642 | 0.642 |
| imports of goods & services | | | | | | | | | |
| AR | 3.022 | 3.022 | 3.022 | 3.022 | 3.006 | 3.006 | 3.006 | 3.006 | 3.006 |
| mean | 0.821* | 0.829* | 0.829* | 0.806** | 0.834* | 0.808* | 0.807* | 0.805* | 0.805* |
| min SIC | 1.124 | 0.971 | 0.906 | 0.895 | 0.990 | 1.008 | 1.090 | 0.938 | 0.956 |
| bayesian | 0.821* | 0.829* | 0.829* | 0.806** | 0.834* | 0.808* | 0.807* | 0.805* | 0.805* |
| gr | 0.865 | 0.923 | 0.811* | 0.823* | 0.911 | 0.834 | 0.879 | 0.907 | 0.899 |
| shrink | 0.858* | 0.840** | 0.839* | 0.817* | 0.956 | 0.856 | 0.881 | 0.882 | 0.877 |
| MMA | 0.917 | 0.887 | 0.816* | 0.812* | 0.858* | 0.809* | 0.864 | 0.830* | 0.822 |
| msfe | 0.787** | 0.795** | 0.790** | 0.768** | 0.801* | 0.778* | 0.779* | 0.775* | 0.774* |
| rank | 0.622** | 0.606** | 0.608** | 0.614** | 0.643** | 0.629** | 0.643** | 0.651** | 0.650** |
| egr | 1.135 | 1.154 | 1.073 | 0.860 | 1.036 | 0.852 | 0.890 | 0.876 | 0.875 |
| government consumption | | | | | | | | | |
| AR | 0.720 | 0.720 | 0.720 | 0.720 | 0.723 | 0.723 | 0.723 | 0.723 | 0.723 |
| mean | 0.960 | 1.014 | 1.018 | 0.972 | 0.965 | 0.967 | 0.962* | 0.976 | 0.990 |
| min SIC | 1.126 | 1.128 | 1.226 | 1.216 | 1.230 | 1.320 | 1.172 | 1.172 | 1.137 |
| bayesian | 0.960 | 1.016 | 1.020 | 0.975 | 0.965 | 0.968 | 0.964 | 0.977 | 0.991 |
| gr | 0.988 | 1.003 | 1.012 | 0.960 | 1.009 | 1.052 | 1.094 | 0.947 | 0.948 |
| shrink | 0.994 | 1.023 | 1.064 | 1.001 | 1.261 | 1.203 | 1.203 | 0.954 | 0.970 |
| MMA | 0.976 | 1.013 | 1.017 | 0.958 | 1.167 | 1.087 | 1.057 | 1.163 | 1.224 |
| msfe | 0.953* | 1.002 | 1.000 | 0.958 | 0.942** | 0.944** | 0.941** | 0.953** | 0.967* |
| rank | 0.939* | 0.945 | 0.895** | 0.886** | 0.792*** | 0.765*** | 0.780*** | 0.771*** | 0.763*** |
| egr | 1.200 | 1.025 | 1.004 | 1.043 | 1.013 | 1.084 | 1.107 | 1.107 | 1.055 |
| construction investment | | | | | | | | | |
| AR | 3.052 | 3.052 | 3.052 | 3.052 | 3.058 | 3.058 | 3.058 | 3.058 | 3.058 |
| mean | 0.941** | 0.952* | 0.964 | 0.962* | 0.982 | 0.964 | 0.946* | 0.938** | 0.947* |
| min SIC | 0.725** | 0.725** | 0.801** | 0.801** | 0.918 | 0.796* | 0.783* | 0.762* | 0.766** |
| bayesian | 0.940** | 0.950* | 0.964 | 0.962* | 0.981 | 0.962 | 0.944* | 0.936** | 0.945** |

To be continued...

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|---|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| gr | 1.015 | 0.952 | 0.925* | 0.948 | 0.849** | 0.713*** | 0.736** | 0.642*** | 0.702** |
| shrink | 1.019 | 0.986 | 0.975 | 0.967 | 0.845*** | 0.731*** | 0.759** | 0.655*** | 0.731** |
| MMA | 1.060 | 0.990 | 0.962* | 0.963 | 0.942 | 1.048 | 1.034 | 0.932 | 0.942 |
| msfe | 0.881*** | 0.889*** | 0.941** | 0.934** | 0.927** | 0.892** | 0.858*** | 0.840*** | 0.859*** |
| rank | 0.684*** | 0.686*** | 0.797*** | 0.761*** | 0.663*** | 0.636*** | 0.618*** | 0.598*** | 0.630*** |
| egr | 0.781 ** | 0.778 ** | 0.947 | 0.950 | 0.918 | 0.945 | 0.874 | 0.780 * | 0.822 * |
| remaining gross fixed investment | | | | | | | | | |
| AR | 4.429 | 4.429 | 4.429 | 4.429 | 4.404 | 4.404 | 4.404 | 4.404 | 4.404 |
| mean | 0.934 | 0.931 | 0.922 | 0.890* | 0.839 | 0.814 | 0.807 | 0.806 | 0.808 |
| min SIC | 1.766 | 1.750 | 1.731 | 1.103 | 1.607 | 1.032 | 1.049 | 0.887 | 0.879 |
| bayesian | 0.934 | 0.931 | 0.922 | 0.890* | 0.839 | 0.815 | 0.807 | 0.806 | 0.808 |
| gr | 0.988 | 0.907 | 0.964 | 0.906 | 0.961 | 0.958 | 1.012 | 0.948 | 0.977 |
| shrink | 1.004 | 0.935 | 0.914 | 0.901 | 0.893 | 0.860 | 1.016 | 0.857 | 0.872 |
| MMA | 0.984 | 0.911 | 0.958 | 0.895 | 0.884 | 0.943 | 0.975 | 0.839 | 0.865 |
| msfe | 0.903* | 0.904* | 0.895* | 0.864* | 0.815 | 0.772 | 0.764 | 0.774 | 0.775 |
| rank | 0.750* | 0.761* | 0.744* | 0.715* | 0.681* | 0.643* | 0.623* | 0.642* | 0.643* |
| egr | 1.062 | 0.983 | 1.010 | 0.946 | 0.955 | 0.987 | 0.993 | 0.821 | 0.821 |
| inventories | | | | | | | | | |
| AR | 4.819 | 4.819 | 4.819 | 4.819 | 4.880 | 4.880 | 4.880 | 4.880 | 4.880 |
| mean | 1.133 | 1.088 | 1.076 | 1.199 | 0.865** | 0.865** | 0.867** | 0.871** | 0.871** |
| min SIC | 1.261 | 1.296 | 1.300 | 1.323 | 1.108 | 1.196 | 1.201 | 1.060 | 1.005 |
| gr | 1.149 | 1.107 | 1.134 | 1.235 | 0.937 | 0.931 | 0.943 | 0.998 | 0.993 |
| bayesian | 1.133 | 1.088 | 1.076 | 1.199 | 0.865** | 0.865** | 0.867** | 0.872** | 0.871** |
| shrink | 1.119 | 1.116 | 1.100 | 1.222 | 0.931 | 0.949 | 0.960 | 0.972 | 0.981 |
| MMA | 1.125 | 1.139 | 1.204 | 1.286 | 0.967 | 0.960 | 0.990 | 1.003 | 0.986 |
| msfe | 1.112 | 1.055 | 1.040 | 1.175 | 0.855** | 0.855** | 0.856** | 0.862** | 0.862** |
| rank | 1.009 | 0.964 | 0.942 | 1.074 | 0.751*** | 0.731*** | 0.728*** | 0.770*** | 0.771*** |
| egr | 1.033 | 1.145 | 1.137 | 1.261 | 0.970 | 0.877 ** | 0.879 ** | 0.930 | 0.924 |

Note: Relative RMFE for GDP components forecasts based on various weighting schemes are shown for the 9 forecast rounds (relative to the corresponding AR forecast given in the respective first line).

Table 8: GDP bottom-up forecast - production approach

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|---|----------|----------|----------|----------|----------|----------|----------|-----------|-----------|
| agriculture, forestry & fishing | | | | | | | | | |
| AR | 6.165 | 6.165 | 6.165 | 6.165 | 6.161 | 6.161 | 6.161 | 6.161 | 6.161 |
| mean | 1.046 | 1.102 | 1.117 | 1.123 | 1.120 | 1.047 | 1.040 | 1.033 | 1.052 |
| min SIC | 1.127 | 1.024 | 1.060 | 1.158 | 1.108 | 1.135 | 1.050 | 1.017 | 1.017 |
| bayesian | 1.046 | 1.102 | 1.117 | 1.123 | 1.120 | 1.047 | 1.041 | 1.034 | 1.052 |
| gr | 1.154 | 1.185 | 1.100 | 1.108 | 1.071 | 1.045 | 1.013 | 1.010 | 1.012 |
| shrink | 1.118 | 1.184 | 1.145 | 1.135 | 1.074 | 1.021 | 0.996 | 1.017 | 1.079 |
| MMA | 1.165 | 1.172 | 1.086 | 1.094 | 1.129 | 1.074 | 1.006 | 1.034 | 1.060 |
| msfe | 1.037 | 1.083 | 1.091 | 1.101 | 1.100 | 1.038 | 1.033 | 1.027 | 1.048 |
| rank | 0.950 | 0.997 | 1.069 | 1.070 | 0.979 | 0.970 | 1.002 | 1.029 | 0.998 |
| egr | 1.020 | 1.034 | 1.105 | 1.046 | 1.025 | 1.057 | 1.040 | 1.042 | 1.028 |
| construction | | | | | | | | | |
| AR | 3.639 | 3.639 | 3.639 | 3.639 | 3.652 | 3.652 | 3.652 | 3.652 | 3.652 |
| mean | 0.994 | 0.977 | 0.991 | 0.982 | 0.999 | 0.983 | 0.973 | 0.976 | 0.973 |
| min SIC | 1.057 | 1.178 | 1.041 | 1.007 | 1.017 | 0.785** | 0.787** | 0.718** | 0.718** |
| bayesian | 0.994 | 0.977 | 0.991 | 0.982 | 0.999 | 0.982 | 0.972 | 0.975 | 0.972 |
| gr | 1.034 | 0.984 | 0.949 | 0.915** | 0.880** | 0.759*** | 0.763*** | 0.721*** | 0.716*** |
| shrink | 1.007 | 0.978* | 0.986 | 0.988 | 0.907** | 0.818*** | 0.794*** | 0.724*** | 0.739*** |
| MMA | 1.004 | 0.957 | 0.936* | 0.900*** | 1.120 | 1.134 | 1.114 | 1.082 | 1.060 |
| msfe | 0.966* | 0.949** | 0.972 | 0.962* | 0.958 | 0.938 | 0.929* | 0.917** | 0.913** |
| rank | 0.775*** | 0.787*** | 0.842*** | 0.775*** | 0.766*** | 0.743*** | 0.730*** | 0.671*** | 0.672*** |
| egr | 1.043 | 1.039 | 1.121 | 1.067 | 0.883 ** | 0.826 ** | 0.894 | 0.727 *** | 0.728 *** |
| financing,renting & corporate services | | | | | | | | | |
| AR | 0.852 | 0.852 | 0.852 | 0.852 | 0.848 | 0.848 | 0.848 | 0.848 | 0.848 |
| mean | 1.000 | 0.982 | 0.964 | 0.946* | 0.946* | 0.951 | 0.932* | 0.938* | 0.945 |
| min SIC | 1.352 | 1.180 | 1.149 | 1.196 | 1.180 | 1.406 | 1.296 | 1.162 | 1.162 |
| bayesian | 1.000 | 0.982 | 0.964 | 0.946* | 0.945* | 0.950 | 0.931* | 0.937* | 0.944 |
| gr | 1.014 | 0.990 | 0.981 | 0.952 | 0.983 | 0.960 | 0.922 | 0.922 | 0.924 |
| shrink | 1.093 | 1.041 | 1.036 | 1.039 | 1.095 | 1.106 | 0.999 | 1.037 | 1.034 |
| MMA | 1.068 | 1.011 | 0.998 | 1.007 | 1.037 | 1.029 | 1.021 | 0.988 | 0.989 |
| msfe | 0.979 | 0.962* | 0.943** | 0.923** | 0.930** | 0.936 | 0.917* | 0.924* | 0.931* |
| rank | 0.879** | 0.870*** | 0.826*** | 0.836** | 0.853** | 0.865** | 0.845** | 0.851** | 0.856** |
| egr | 1.233 | 1.337 | 1.109 | 1.105 | 1.203 | 1.206 | 1.205 | 1.205 | 1.206 |
| producing sector excl. construction | | | | | | | | | |
| AR | 3.354 | 3.354 | 3.354 | 3.354 | 3.315 | 3.315 | 3.315 | 3.315 | 3.315 |
| mean | 1.017 | 0.999 | 0.956 | 0.913 | 0.939 | 0.922 | 0.915 | 0.881 | 0.881 |
| min SIC | 0.912** | 0.904** | 1.508 | 1.180 | 1.175 | 1.045 | 0.988 | 0.985 | 0.985 |
| bayesian | 1.015 | 0.997 | 0.954 | 0.911 | 0.938 | 0.921 | 0.914 | 0.880 | 0.880 |
| gr | 1.249 | 1.101 | 1.043 | 1.095 | 1.188 | 0.783 | 0.788 | 0.635 | 0.636 |
| shrink | 1.169 | 1.080 | 1.011 | 1.050 | 1.203 | 0.798 | 0.789 | 0.632 | 0.635 |
| MMA | 1.359 | 1.167 | 1.112 | 1.079 | 1.165 | 0.778 | 0.776 | 0.608 | 0.608 |
| msfe | 0.926 | 0.911 | 0.867 | 0.827* | 0.882 | 0.857 | 0.849 | 0.782 | 0.782 |
| rank | 0.718* | 0.702* | 0.682* | 0.647* | 0.675 | 0.650* | 0.640* | 0.570* | 0.570* |
| egr | 0.760 * | 0.740 * | 0.763 * | 0.869 | 1.167 | 1.102 | 0.981 | 0.884 | 0.884 |
| public & private service suppliers | | | | | | | | | |
| AR | 0.407 | 0.407 | 0.407 | 0.407 | 0.406 | 0.406 | 0.406 | 0.406 | 0.406 |
| mean | 1.013 | 1.052 | 1.071 | 1.029 | 1.082 | 1.067 | 1.016 | 1.008 | 1.040 |
| min SIC | 1.547 | 1.541 | 1.680 | 1.539 | 1.245 | 1.246 | 1.243 | 1.248 | 1.248 |
| bayesian | 1.015 | 1.053 | 1.073 | 1.031 | 1.081 | 1.066 | 1.013 | 1.007 | 1.038 |

To be continued. . .

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|---|----------|---------|---------|---------|---------|---------|----------|----------|----------|
| gr | 0.966 | 0.938 | 1.040 | 1.003 | 1.147 | 1.135 | 1.021 | 1.062 | 1.072 |
| shrink | 1.201 | 1.206 | 1.177 | 1.131 | 1.292 | 1.275 | 1.182 | 1.161 | 1.161 |
| MMA | 1.029 | 1.071 | 1.090 | 1.040 | 1.178 | 1.030 | 0.968 | 1.027 | 1.035 |
| msfe | 0.972 | 1.011 | 1.041 | 1.011 | 1.049 | 1.029 | 0.985 | 0.975 | 0.997 |
| rank | 0.830*** | 0.883* | 0.926 | 0.922 | 0.883** | 0.888** | 0.829*** | 0.817*** | 0.803*** |
| egr | 1.191 | 1.175 | 1.125 | 1.141 | 1.081 | 1.101 | 1.167 | 1.180 | 1.181 |
| wholesale & retail trade & transport | | | | | | | | | |
| AR | 1.437 | 1.437 | 1.437 | 1.437 | 1.430 | 1.430 | 1.430 | 1.430 | 1.430 |
| mean | 0.950* | 0.887* | 0.929* | 0.908** | 0.865* | 0.851* | 0.847** | 0.813** | 0.816** |
| min SIC | 1.134 | 0.832 | 0.798 | 1.137 | 1.126 | 1.121 | 0.913 | 0.951 | 0.951 |
| bayesian | 0.951 | 0.887* | 0.929* | 0.910** | 0.865* | 0.851* | 0.847** | 0.813** | 0.816** |
| gr | 0.948 | 0.949 | 0.972 | 0.962 | 0.973 | 1.001 | 1.024 | 0.872 | 0.903 |
| shrink | 0.939 | 0.939 | 0.950 | 0.946 | 1.072 | 1.027 | 1.052 | 0.895 | 0.896 |
| MMA | 0.951 | 0.947 | 0.942 | 0.955 | 0.725* | 1.232 | 1.216 | 0.988 | 1.010 |
| msfe | 0.917* | 0.847* | 0.870* | 0.840** | 0.819* | 0.801* | 0.798** | 0.759** | 0.762** |
| rank | 0.804** | 0.727** | 0.705** | 0.681** | 0.676** | 0.677* | 0.667** | 0.596** | 0.603** |
| egr | 1.077 | 1.033 | 1.029 | 1.108 | 0.903 | 0.801 | 0.825 | 0.880 | 0.913 |
| taxes- subsidies | | | | | | | | | |
| AR | 3.124 | 3.124 | 3.124 | 3.124 | 3.149 | 3.149 | 3.149 | 3.149 | 3.149 |
| mean | 1.034 | 1.165 | 1.076 | 0.933 | 0.971 | 0.981 | 0.975 | 0.966 | 0.964 |
| min SIC | 1.458 | 1.385 | 1.381 | 1.516 | 0.987 | 1.096 | 1.119 | 1.102 | 1.098 |
| bayesian | 1.034 | 1.165 | 1.077 | 0.934 | 0.971 | 0.981 | 0.975 | 0.966 | 0.964 |
| gr | 1.185 | 1.114 | 1.100 | 1.131 | 0.896* | 0.980 | 0.988 | 0.962 | 0.952 |
| shrink | 1.091 | 1.126 | 1.055 | 1.000 | 0.870** | 1.024 | 1.017 | 0.936** | 0.931* |
| MMA | 1.143 | 1.054 | 1.202 | 1.211 | 1.018 | 1.251 | 1.204 | 1.084 | 1.180 |
| msfe | 1.000 | 1.130 | 1.039 | 0.884 | 0.933 | 0.947 | 0.942 | 0.934* | 0.932 |
| rank | 0.956 | 1.103 | 0.996 | 0.796* | 0.706** | 0.746** | 0.782** | 0.766*** | 0.755*** |
| egr | 1.016 | 1.105 | 1.017 | 1.032 | 1.039 | 1.106 | 1.011 | 1.033 | 1.047 |

Note: Relative RMFE for GDP components forecasts based on various weighting schemes are shown for the 9 forecast rounds (relative to the corresponding AR forecast given in the respective first line).

Table 9: GDP bottom-up forecast - demand approach

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|--|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| consumer expenditure | | | | | | | | | |
| AR | 0.540 | 0.540 | 0.540 | 0.540 | 0.543 | 0.543 | 0.543 | 0.543 | 0.543 |
| mean | 1.063 | 1.076 | 1.125 | 1.057 | 1.029 | 1.023 | 1.033 | 0.876 * | 0.874 * |
| min SIC | 1.221 | 1.136 | 1.350 | 1.303 | 1.336 | 1.391 | 1.396 | 1.405 | 1.405 |
| bayesian | 1.066 | 1.078 | 1.126 | 1.058 | 1.030 | 1.028 | 1.036 | 0.880 * | 0.878 * |
| gr | 1.085 | 1.116 | 1.144 | 1.030 | 1.025 | 1.098 | 1.124 | 1.097 | 1.096 |
| shrink | 1.071 | 1.135 | 1.144 | 1.088 | 1.286 | 1.401 | 1.404 | 1.412 | 1.412 |
| MMA | 1.185 | 1.136 | 1.209 | 1.097 | 1.161 | 1.186 | 1.210 | 1.119 | 1.149 |
| msfe | 1.011 | 1.044 | 1.095 | 1.035 | 0.975 | 0.963 | 0.970 | 0.801 *** | 0.802 *** |
| rank | 0.830 ** | 0.894 * | 0.977 | 0.905 | 0.865 * | 0.795 *** | 0.789 *** | 0.649 *** | 0.650 *** |
| egr | 1.333 | 1.083 | 1.161 | 1.095 | 1.090 | 1.183 | 1.198 | 1.068 | 1.068 |
| exports of goods & services | | | | | | | | | |
| AR | 2.433 | 2.433 | 2.433 | 2.433 | 2.405 | 2.405 | 2.405 | 2.405 | 2.405 |
| mean | 0.853 ** | 0.835 ** | 0.831 * | 0.790 ** | 0.794 ** | 0.778 * | 0.775 * | 0.758 * | 0.760 * |
| min SIC | 0.944 | 0.958 | 0.974 | 1.248 | 1.391 | 0.928 | 0.925 | 0.655 * | 0.655 * |
| bayesian | 0.854 ** | 0.835 ** | 0.831 * | 0.790 ** | 0.794 ** | 0.778 * | 0.774 * | 0.758 * | 0.760 * |
| gr | 0.999 | 0.910 | 0.901 | 0.936 | 1.021 | 0.879 | 0.798 | 0.791 | 0.798 |
| shrink | 0.889 ** | 0.874 ** | 0.859 ** | 0.854 ** | 1.003 | 1.022 | 0.850 * | 0.838 | 0.858 |
| MMA | 0.993 | 0.914 | 0.921 | 0.853 * | 0.989 | 1.039 | 0.907 | 0.948 | 0.947 |
| msfe | 0.825 ** | 0.806 ** | 0.805 ** | 0.763 ** | 0.760 ** | 0.738 ** | 0.730 ** | 0.710 ** | 0.712 ** |
| rank | 0.713 *** | 0.697 *** | 0.717 ** | 0.659 *** | 0.647 ** | 0.627 ** | 0.614 ** | 0.598 ** | 0.598 ** |
| egr | 1.020 | 1.020 | 0.996 | 0.960 | 0.825 | 0.809 | 0.790 * | 0.800 | 0.800 |
| imports of goods & services | | | | | | | | | |
| AR | 2.230 | 2.230 | 2.230 | 2.230 | 2.229 | 2.229 | 2.229 | 2.229 | 2.229 |
| mean | 0.902 | 0.915 | 0.913 | 0.891 * | 0.917 | 0.892 | 0.889 | 0.891 | 0.892 |
| min SIC | 1.043 | 0.942 | 0.901 * | 0.995 | 0.962 | 0.939 | 1.079 | 0.901 | 0.907 |
| bayesian | 0.902 | 0.915 | 0.913 | 0.891 * | 0.917 | 0.892 | 0.889 | 0.891 | 0.892 |
| gr | 0.900 | 0.927 | 0.859 | 0.890 | 0.994 | 0.957 | 0.961 | 0.981 | 0.970 |
| shrink | 0.887 * | 0.883 * | 0.908 | 0.887 * | 1.052 | 0.978 | 0.956 | 0.962 | 0.960 |
| MMA | 0.906 | 0.882 * | 0.860 | 0.877 | 0.921 | 0.885 | 0.942 | 0.913 | 0.913 |
| msfe | 0.866 * | 0.880 * | 0.875 * | 0.854 * | 0.878 | 0.852 | 0.850 * | 0.852 | 0.853 |
| rank | 0.683 ** | 0.689 ** | 0.685 ** | 0.685 ** | 0.696 ** | 0.682 ** | 0.699 ** | 0.703 ** | 0.699 ** |
| egr | 1.102 | 1.110 | 1.144 | 0.963 | 1.089 | 0.894 | 0.940 | 0.896 | 0.895 |
| government consumption | | | | | | | | | |
| AR | 0.607 | 0.607 | 0.607 | 0.607 | 0.609 | 0.609 | 0.609 | 0.609 | 0.609 |
| mean | 0.894 ** | 0.951 | 0.973 | 0.912 ** | 0.904 ** | 0.911 * | 0.902 ** | 0.922 ** | 0.936 * |
| min SIC | 1.061 | 1.063 | 1.086 | 1.064 | 1.142 | 1.253 | 1.079 | 1.091 | 1.074 |
| bayesian | 0.894 ** | 0.952 | 0.975 | 0.915 * | 0.904 ** | 0.911 * | 0.903 ** | 0.923 ** | 0.936 * |
| gr | 0.898 * | 0.923 * | 0.960 | 0.881 | 0.940 | 0.986 | 1.037 | 0.875 ** | 0.857 ** |
| shrink | 0.884 ** | 0.922 * | 1.002 | 0.932 | 1.071 | 1.131 | 1.139 | 0.879 * | 0.881 ** |
| MMA | 0.889 ** | 0.932 | 0.982 | 0.886 | 1.099 | 1.045 | 0.954 | 1.106 | 1.155 |
| msfe | 0.873 ** | 0.933 | 0.947 | 0.887 ** | 0.878 ** | 0.890 ** | 0.892 ** | 0.900 ** | 0.915 ** |
| rank | 0.864 ** | 0.846 ** | 0.830 *** | 0.831 *** | 0.726 *** | 0.699 *** | 0.735 *** | 0.707 *** | 0.701 *** |
| egr | 1.144 | 0.968 | 0.943 * | 1.042 | 1.003 | 1.062 | 1.096 | 1.091 | 1.030 |
| construction investment | | | | | | | | | |
| AR | 2.350 | 2.350 | 2.350 | 2.350 | 2.359 | 2.359 | 2.359 | 2.359 | 2.359 |
| mean | 1.002 | 1.006 | 1.007 | 1.003 | 1.034 | 1.046 | 1.020 | 1.004 | 1.019 |
| min SIC | 0.788 | 0.788 | 0.916 | 0.916 | 0.981 | 0.823 | 0.801 | 0.774 | 0.808 * |
| bayesian | 1.001 | 1.005 | 1.006 | 1.003 | 1.034 | 1.044 | 1.018 | 1.003 | 1.017 |

To be continued. . .

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|---|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| gr | 1.075 | 1.017 | 0.994 | 0.977 | 0.919 | 0.812 ** | 0.822 * | 0.710 ** | 0.788 ** |
| shrink | 1.068 | 1.030 | 1.021 | 0.996 | 0.930 * | 0.825 ** | 0.843 * | 0.723 ** | 0.809 * |
| MMA | 1.151 | 1.059 | 1.015 | 0.981 | 0.981 | 1.083 | 1.061 | 0.962 | 0.983 |
| msfe | 0.940 * | 0.947 * | 0.984 | 0.975 | 0.984 | 0.978 | 0.937 * | 0.910 ** | 0.932 * |
| rank | 0.738 ** | 0.761 ** | 0.854 ** | 0.805 *** | 0.754 *** | 0.726 *** | 0.702 *** | 0.642 *** | 0.680 *** |
| egr | 0.868 | 0.861 | 0.989 | 0.999 | 0.958 | 1.027 | 0.977 | 0.822 * | 0.888 |
| remaining gross fixed investment | | | | | | | | | |
| AR | 2.671 | 2.671 | 2.671 | 2.671 | 2.648 | 2.648 | 2.648 | 2.648 | 2.648 |
| mean | 0.922 | 0.924 | 0.911 | 0.887 | 0.898 | 0.877 | 0.865 | 0.857 | 0.855 |
| min SIC | 1.419 | 1.377 | 1.519 | 1.181 | 1.525 | 1.223 | 1.235 | 1.067 | 1.044 |
| bayesian | 0.922 | 0.924 | 0.911 | 0.887 | 0.898 | 0.877 | 0.865 | 0.857 | 0.855 |
| gr | 1.015 | 0.976 | 0.983 | 0.944 | 1.081 | 0.978 | 1.008 | 1.000 | 1.053 |
| shrink | 1.065 | 0.999 | 0.964 | 0.994 | 0.979 | 0.929 | 1.065 | 0.936 | 0.950 |
| MMA | 1.027 | 0.975 | 0.964 | 0.965 | 0.951 | 0.967 | 0.972 | 0.924 | 0.997 |
| msfe | 0.890 | 0.894 | 0.880 | 0.860 * | 0.871 | 0.841 * | 0.828 * | 0.827 * | 0.826 * |
| rank | 0.739 *** | 0.740 *** | 0.715 *** | 0.740 *** | 0.709 *** | 0.715 ** | 0.695 *** | 0.715 ** | 0.715 ** |
| egr | 1.103 | 1.093 | 1.133 | 1.047 | 1.118 | 1.008 | 1.017 | 1.023 | 1.025 |
| inventories | | | | | | | | | |
| AR | 3.660 | 3.660 | 3.660 | 3.660 | 3.721 | 3.721 | 3.721 | 3.721 | 3.721 |
| mean | 1.186 | 1.134 | 1.137 | 1.225 | 0.847 ** | 0.848 ** | 0.849 ** | 0.854 ** | 0.853 ** |
| min SIC | 1.317 | 1.429 | 1.453 | 1.369 | 1.140 | 1.054 | 1.080 | 1.054 | 1.017 |
| bayesian | 1.186 | 1.134 | 1.137 | 1.225 | 0.847 ** | 0.848 ** | 0.849 ** | 0.854 ** | 0.853 ** |
| gr | 1.217 | 1.154 | 1.171 | 1.259 | 0.893 ** | 0.926 | 0.936 | 0.934 | 0.940 |
| shrink | 1.183 | 1.157 | 1.152 | 1.233 | 0.898 ** | 0.933 | 0.937 | 0.909 * | 0.930 |
| MMA | 1.192 | 1.188 | 1.244 | 1.304 | 0.938 | 0.953 | 0.958 | 0.945 | 0.938 |
| msfe | 1.161 | 1.105 | 1.099 | 1.194 | 0.836 ** | 0.837 ** | 0.838 ** | 0.844 ** | 0.844 ** |
| rank | 1.007 | 1.020 | 0.982 | 1.088 | 0.720 *** | 0.705 *** | 0.701 *** | 0.732 *** | 0.733 *** |
| egr | 1.053 | 1.213 | 1.204 | 1.334 | 0.951 | 0.873 ** | 0.868 * | 0.905 | 0.900 |

Note: Relative MAFE for GDP components forecasts based on various weighting schemes are shown for the 9 forecast rounds (relative to the corresponding AR forecast given in the respective first line).

Table 10: GDP bottom-up forecast - production approach

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|---|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| agriculture, forestry & fishing | | | | | | | | | |
| AR | 2.924 | 2.924 | 2.924 | 2.924 | 2.929 | 2.929 | 2.929 | 2.929 | 2.929 |
| mean | 1.191 | 1.293 | 1.306 | 1.207 | 1.187 | 1.168 | 1.138 | 1.062 | 1.078 |
| min SIC | 1.516 | 1.278 | 1.359 | 1.486 | 1.290 | 1.392 | 1.293 | 1.204 | 1.204 |
| bayesian | 1.190 | 1.293 | 1.306 | 1.207 | 1.187 | 1.168 | 1.138 | 1.062 | 1.078 |
| gr | 1.463 | 1.504 | 1.272 | 1.269 | 1.254 | 1.283 | 1.142 | 1.040 | 1.032 |
| shrink | 1.309 | 1.449 | 1.362 | 1.156 | 1.115 | 1.134 | 1.106 | 1.103 | 1.133 |
| MMA | 1.461 | 1.475 | 1.220 | 1.223 | 1.284 | 1.175 | 1.087 | 1.149 | 1.178 |
| msfe | 1.168 | 1.255 | 1.259 | 1.161 | 1.155 | 1.147 | 1.120 | 1.047 | 1.068 |
| rank | 0.942 | 1.032 | 1.212 | 1.112 | 0.986 | 0.996 | 1.116 | 1.129 | 1.022 |
| egr | 1.056 | 1.040 | 1.174 | 1.066 | 1.049 | 1.132 | 1.127 | 1.133 | 1.046 |
| construction | | | | | | | | | |
| AR | 2.629 | 2.629 | 2.629 | 2.629 | 2.621 | 2.621 | 2.621 | 2.621 | 2.621 |
| mean | 1.024 | 1.006 | 1.002 | 1.013 | 1.062 | 1.043 | 1.042 | 1.044 | 1.033 |
| min SIC | 1.116 | 1.230 | 1.152 | 1.108 | 1.112 | 0.846* | 0.847* | 0.793** | 0.793** |
| bayesian | 1.024 | 1.006 | 1.003 | 1.014 | 1.062 | 1.043 | 1.041 | 1.043 | 1.032 |
| gr | 1.034 | 0.993 | 0.994 | 0.972 | 0.949 | 0.745*** | 0.758*** | 0.735** | 0.721*** |
| shrink | 0.976 | 0.965* | 0.983 | 0.986 | 0.927 | 0.840** | 0.826** | 0.751*** | 0.777*** |
| MMA | 0.981 | 0.940* | 0.980 | 0.961 | 1.167 | 1.195 | 1.129 | 1.122 | 1.096 |
| msfe | 0.989 | 0.973 | 0.980 | 0.988 | 1.003 | 0.987 | 0.986 | 0.967 | 0.954 |
| rank | 0.774*** | 0.787*** | 0.836*** | 0.751*** | 0.809*** | 0.756*** | 0.755*** | 0.696*** | 0.711*** |
| egr | 1.058 | 1.076 | 1.157 | 1.139 | 0.973 | 0.927 | 0.934 | 0.768*** | 0.769*** |
| financing,renting & corporate services | | | | | | | | | |
| AR | 0.654 | 0.654 | 0.654 | 0.654 | 0.647 | 0.647 | 0.647 | 0.647 | 0.647 |
| mean | 1.062 | 1.035 | 0.992 | 0.978 | 0.984 | 0.989 | 0.974 | 0.980 | 0.978 |
| min SIC | 1.440 | 1.255 | 1.172 | 1.231 | 1.237 | 1.482 | 1.291 | 1.199 | 1.199 |
| bayesian | 1.062 | 1.035 | 0.992 | 0.977 | 0.982 | 0.987 | 0.972 | 0.977 | 0.976 |
| gr | 1.046 | 1.036 | 0.989 | 0.983 | 0.967 | 0.939 | 0.902 | 0.876 | 0.874 |
| shrink | 1.176 | 1.122 | 1.092 | 1.130 | 1.110 | 1.152 | 1.019 | 1.027 | 1.025 |
| MMA | 1.097 | 1.024 | 0.993 | 1.003 | 1.111 | 1.074 | 1.086 | 1.078 | 1.075 |
| msfe | 1.031 | 1.005 | 0.963 | 0.945 | 0.965 | 0.970 | 0.953 | 0.960 | 0.960 |
| rank | 0.887* | 0.870*** | 0.815*** | 0.818** | 0.873** | 0.884* | 0.839** | 0.844** | 0.850** |
| egr | 1.186 | 1.234 | 1.100 | 1.144 | 1.246 | 1.243 | 1.237 | 1.240 | 1.242 |
| producing sector excl. construction | | | | | | | | | |
| AR | 2.047 | 2.047 | 2.047 | 2.047 | 2.012 | 2.012 | 2.012 | 2.012 | 2.012 |
| mean | 1.009 | 0.996 | 0.961 | 0.935 | 0.942 | 0.923 | 0.915 | 0.893 | 0.893 |
| min SIC | 0.841*** | 0.828*** | 1.173 | 1.052 | 1.056 | 1.035 | 0.924 | 1.019 | 1.019 |
| bayesian | 1.008 | 0.995 | 0.960 | 0.934 | 0.942 | 0.921 | 0.914 | 0.891 | 0.891 |
| gr | 1.195 | 1.106 | 1.046 | 1.042 | 1.116 | 0.792 | 0.820 | 0.771 | 0.771 |
| shrink | 1.115 | 1.085 | 1.052 | 1.074 | 1.183 | 0.815 | 0.799 | 0.766 | 0.769 |
| MMA | 1.206 | 1.147 | 0.993 | 0.995 | 1.041 | 0.756* | 0.774 | 0.736 | 0.735 |
| msfe | 0.935 | 0.922 | 0.883 | 0.860* | 0.881 | 0.857 | 0.848 | 0.805* | 0.804* |
| rank | 0.737*** | 0.716*** | 0.690*** | 0.687*** | 0.689** | 0.656** | 0.639** | 0.613** | 0.613** |
| egr | 0.801** | 0.765** | 0.813* | 0.945 | 0.934 | 1.019 | 0.946 | 0.918 | 0.918 |
| public & private service suppliers | | | | | | | | | |
| AR | 0.313 | 0.313 | 0.313 | 0.313 | 0.312 | 0.312 | 0.312 | 0.312 | 0.312 |
| mean | 0.995 | 1.016 | 1.034 | 1.008 | 1.095 | 1.065 | 1.015 | 1.029 | 1.064 |
| min SIC | 1.543 | 1.517 | 1.736 | 1.542 | 1.271 | 1.291 | 1.288 | 1.281 | 1.281 |
| bayesian | 0.999 | 1.019 | 1.039 | 1.011 | 1.094 | 1.066 | 1.013 | 1.028 | 1.062 |

To be continued. ...

| | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
|---|---------|----------|----------|-----------|-----------|-----------|-----------|-----------|----------|
| gr | 0.932 | 0.916 | 1.044 | 1.008 | 1.175 | 1.161 | 1.048 | 1.111 | 1.122 |
| shrink | 1.207 | 1.218 | 1.244 | 1.202 | 1.335 | 1.320 | 1.195 | 1.118 | 1.118 |
| MMA | 0.962 | 1.048 | 1.049 | 1.007 | 1.204 | 1.053 | 1.052 | 1.087 | 1.095 |
| msfe | 0.955 | 0.970 | 1.009 | 0.998 | 1.066 | 1.033 | 0.985 | 0.986 | 1.006 |
| rank | 0.877** | 0.927 | 0.938 | 0.951 | 0.907** | 0.880*** | 0.836*** | 0.832*** | 0.799** |
| egr | 1.252 | 1.244 | 1.165 | 1.184 | 1.120 | 1.144 | 1.181 | 1.194 | 1.169 |
| wholesale & retail trade & transport | | | | | | | | | |
| AR | 0.973 | 0.973 | 0.973 | 0.973 | 0.968 | 0.968 | 0.968 | 0.968 | 0.968 |
| mean | 1.001 | 0.955 | 0.986 | 0.964 | 0.906* | 0.899** | 0.889** | 0.848** | 0.850** |
| min SIC | 1.166 | 0.901 | 0.864 | 1.154 | 1.219 | 1.194 | 1.076 | 1.112 | 1.112 |
| bayesian | 1.002 | 0.956 | 0.986 | 0.965 | 0.906* | 0.899** | 0.890** | 0.848** | 0.850** |
| gr | 0.986 | 0.985 | 1.058 | 1.103 | 1.056 | 1.084 | 1.136 | 0.946 | 0.989 |
| shrink | 1.016 | 0.991 | 1.054 | 1.103 | 1.150 | 1.145 | 1.197 | 0.993 | 1.000 |
| MMA | 1.005 | 0.999 | 1.027 | 1.081 | 0.836* | 1.179 | 1.172 | 0.993 | 1.021 |
| msfe | 0.974 | 0.920* | 0.932* | 0.905** | 0.858** | 0.850** | 0.844** | 0.794** | 0.796** |
| rank | 0.848** | 0.749*** | 0.740*** | 0.767** | 0.720*** | 0.729** | 0.719*** | 0.631*** | 0.638*** |
| egr | 1.079 | 1.037 | 1.100 | 1.211 | 1.025 | 0.877 | 0.918 | 0.956 | 0.994 |
| taxes- subsidies | | | | | | | | | |
| AR | 2.461 | 2.461 | 2.461 | 2.461 | 2.479 | 2.479 | 2.479 | 2.479 | 2.479 |
| mean | 1.024 | 1.155 | 1.090 | 0.981 | 0.915 | 0.930 | 0.919* | 0.907* | 0.904** |
| min SIC | 1.301 | 1.390 | 1.392 | 1.453 | 0.941 | 1.030 | 1.017 | 1.025 | 1.017 |
| bayesian | 1.024 | 1.155 | 1.091 | 0.981 | 0.915 | 0.930 | 0.919* | 0.907* | 0.904** |
| gr | 1.170 | 1.104 | 1.061 | 1.083 | 0.872* | 0.957 | 0.960 | 0.919 | 0.913 |
| shrink | 1.074 | 1.108 | 1.031 | 1.002 | 0.849*** | 0.970 | 0.953 | 0.873*** | 0.862*** |
| MMA | 1.112 | 1.055 | 1.207 | 1.193 | 1.019 | 1.124 | 1.076 | 1.062 | 1.181 |
| msfe | 0.986 | 1.109 | 1.038 | 0.920 | 0.880** | 0.894** | 0.891** | 0.881** | 0.876** |
| rank | 0.892** | 1.004 | 0.903** | 0.797 *** | 0.699 *** | 0.707 *** | 0.743 *** | 0.731 *** | 0.697*** |
| egr | 1.024 | 1.085 | 0.979 | 1.006 | 1.018 | 1.122 | 0.999 | 1.057 | 1.103 |

Note: Relative RMFE for GDP components forecasts based on various weighting schemes are shown for the 9 forecast rounds (relative to the corresponding AR forecast given in the respective first line).