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

Katja Drechsel and Rolf Scheufele

SCHWEIZERISCHE NATIONALBANK
BANQUE NATIONALE SUISSE
BANCA NAZIONALE SVIZZERA
BANCA NAZIUNALA SVIZRA
SWISS NATIONAL BANK

2012-16

Swiss National Bank Working Papers

The views expressed in this paper are those of the author(s) and do not necessarily represent those of the Swiss National Bank. Working Papers describe research in progress. Their aim is to elicit comments and to further debate.

Copyright ©
The Swiss National Bank (SNB) respects all third-party rights, in particular rights relating to works protected by copyright (information or data, wordings and depictions, to the extent that these are of an individual character).
SNB publications containing a reference to a copyright (© Swiss National Bank/SNB, Zurich/year, or similar) may, under copyright law, only be used (reproduced, used via the internet, etc.) for non-commercial purposes and provided that the source is mentioned. Their use for commercial purposes is only permitted with the prior express consent of the SNB.
General information and data published without reference to a copyright may be used without mentioning the source.
To the extent that the information and data clearly derive from outside sources, the users of such information and data are obliged to respect any existing copyrights and to obtain the right of use from the relevant outside source themselves.

Limitation of liability
The SNB accepts no responsibility for any information it provides. Under no circumstances will it accept any liability for losses or damage which may result from the use of such information. This limitation of liability applies, in particular, to the topicality, accuracy, validity and availability of the information.

ISSN 1660-7716 (printed version)
ISSN 1660-7724 (online version)

© 2012 by Swiss National Bank, Börsenstrasse 15, P.O. Box, CH-8022 Zurich

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

Katja Drechsel† and Rolf Scheufele‡

November 2012

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 to retrace the driving forces of the forecast and hence enables the interpretability of the forecast outcome.

JEL Classification: E32, E37, C52, C53

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

*We would like to thank Antonello D'Agostino, Christian Schumacher, Atilim Seymen and an anonymous referee as well as the participants of the Annual International Symposium on Forecasting 2011, the Annual International Conference on Macroeconomic Analysis 2011, the Annual Conference of the German Economic Association 2011, the $(EC)^2$ Conference 2011, the CSDA International Conference on Computational and Financial Econometrics 2011 and the ESEM Annual Meeting 2012 for helpful comments and suggestions. The views expressed in this paper are those of the authors and not necessarily those of the Swiss National Bank.

†IWH Halle, Kleine Maerkerstrasse 8, 06108 Halle (Saale), Germany, email: `Katja.Drechsel@iwh-halle.de`

‡Swiss National Bank (SNB), Boersenstrasse 15, 8022 Zurich, Switzerland, email: `Rolf.Scheufele@snb.ch`

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 and the recent past since no official statistics are available for this period. The problem of predicting the present and the very near future is often labelled as *nowcasting* (see Banbura *et al.*, 2010) and forecasting the recent past as *backcasting*.

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

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

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,...). Thus this paper is related to other studies that analyze contemporaneous aggregation issues. In the past decade this subject has received new attention through the comparison of the forecast accuracy of aggregating country-specific forecasts versus forecasts based on aggregated euro area wide data (see, Marcellino *et al.*, 2003, for an example). However, the effects of contemporaneous aggregation of (sub)components for time-series data in applied empirical work has not received much attention most recently.[2]

For GDP, the direct approach, namely forecasting aggregate GDP, 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 typically 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 many practitioners (see, Cors and Kouzine, 2003) since many monthly indicators are more closely related to subcomponents of production (mainly manufacturing output) than to aggregate GDP. Forecasting subcomponents through the demand side is often done by large-scale macroeconomic models (see, e.g. Fair and Shiller, 1990). The main contribution of this paper is to analyze rigorously the out-of-sample forecasting accuracy of the different procedures: direct vs. bottom-up approaches. As a 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 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 can-

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

didate variable 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 industries).

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

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

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 $\hat{y}_{it}$ $(i = 1, ..., n)$ 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 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.

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

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 to 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 the 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 macroeconometric 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 is defined as the value of goods and services produced by a particular country in a given period and there are various ways to decompose it into parts, such that the sum of the components equals the national product.[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 made by Parigi and Schlitzer (1995) for Italy, Baffigi *et al.* (2004) for the euro area and Golinelli and Parigi (2007) for the G7 countries. The 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

[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 kinds of income.

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 which 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), inventories[7] (INV) and exports (X) minus imports (M). Note that we disaggregate gross fixed investment into two separate components because we expect that building investment is driven by different factors than equipment investment. The first component is construction investment which includes both residential and non-residential building investments. The second component is 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.

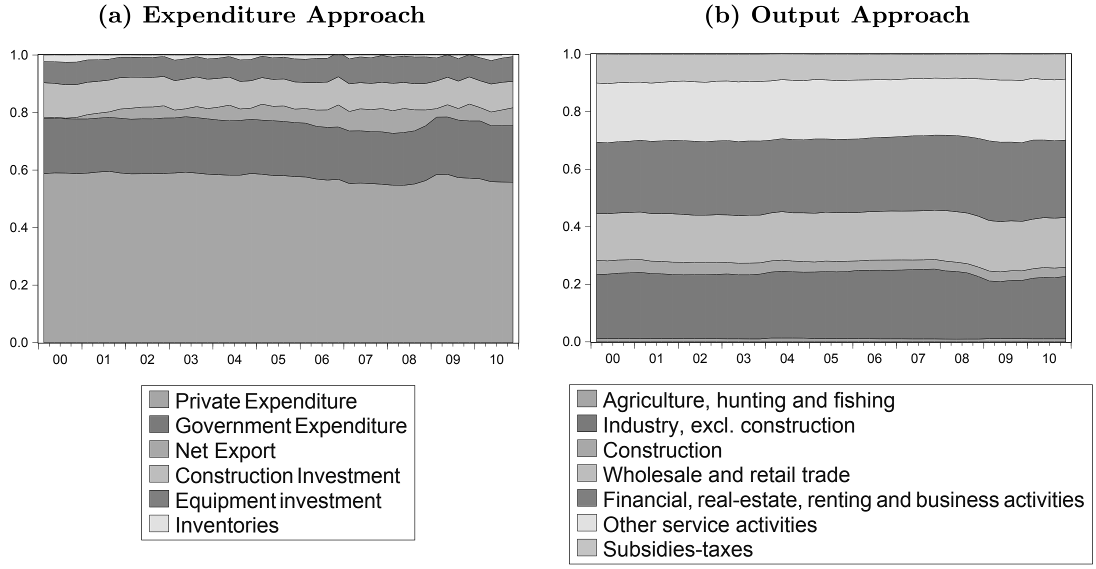
The corresponding GDP growth forecast from the expenditure side can be derived from the growth forecast of each component times the corresponding GDP share. This implies that $\hat{y}^{agg}_{demand,t} \approx \sum_i^n \hat{w}_{it}\hat{y}_{it}$, where $\hat{y}_i$ is the growth forecast of the ith component (out of $n = 7$ components) and $\hat{w}_{it}$ are the estimated weights. Since we apply real quantities, this relationships holds only approximately due to chained weighting.[8] The weights are computed as a moving average of the most recent

[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

[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.

Figure 1: Share of GDP



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

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]

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

[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.

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.

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

[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.

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 GDP 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.

Figure 2: Data releases and forecasting rounds

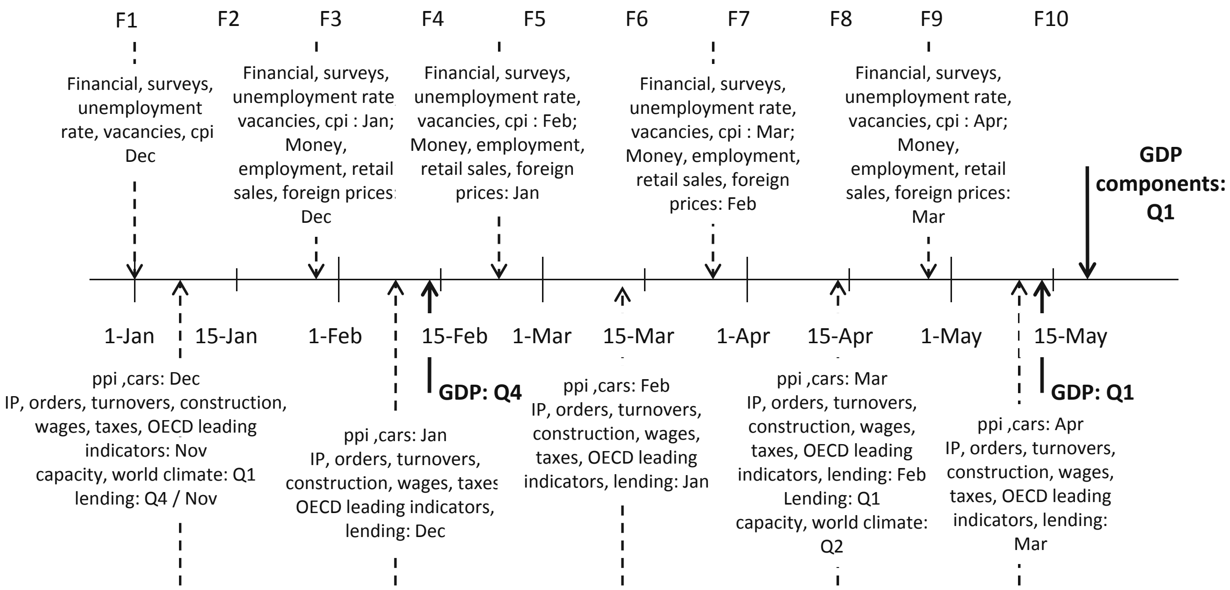


Table 2 shows the structure of our pseudo real-time forecasting exercise for the first quarter as an illustration. Starting with the first forecast, i.e. at the beginning of the first month of a quarter

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 are using actual data that do not take into account the effects of data revisions ("pseudo real time data").

(e.g. January 1^{st}), 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 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) 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

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

[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.

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:

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

where q is the polynomial degree ($q < K$) which can be substantially lower than K. Even with very small q many flexible forms can be approximated.[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 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 ($l = 0, \frac{1}{3}, \frac{2}{3}, \frac{3}{3}, ...$). 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

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

so that

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

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

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

[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: $b(k;\theta) = \frac{exp\left(\theta_1 k + \theta_2 k^2\right)}{\sum_{k=1}^{K} exp\left(\theta_1 k + \theta_2 k^2\right)}$. 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.

[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.

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:

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

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 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.

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

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

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

where $\omega_{i,t}$ 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 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 $M_1, ..., M_n$ (see Stock and Watson, 2006, section 5).[20] Then the predictive probability density of y_t is given by

[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).

[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).

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

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

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

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

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

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

[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.

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:

$$Q = (y - F\omega)^{'}(y - F\omega), \tag{12}$$

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

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

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:

$$\hat{\gamma} = \hat{\sigma}^2/\hat{\sigma}_\omega^2, \tag{14}$$

where

[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 $\hat{D}_\epsilon$ 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.

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

$\hat{\sigma}^2$ 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 of the forecasts is large or when the R^2 given the OLS weights is small. Computationally the shrinked weights (*(v)* shrink) are obtained by minimizing

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

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

$$C = (y - F\omega)^{'}(y - F\omega) + \omega^{'}Ks^2, \tag{16}$$

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

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

where $\lambda_{it} = \sum_{s=T_1}^{t-h} \delta^{t-s} \left(\hat{e}_{i,s}\right)^2$ 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 $S_{it} = \sum_{s=T_1}^{t-h} \left(\hat{e}_{i,s}\right)^2$. For each model, i, the rank for a h-step ahead forecast up to time t is then assessed by $\mathcal{R}_{t,t-h,i} = f(S_{1t}, ..., S_{nt})$. 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

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

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

[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.

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 $\widehat{y}_{i,t}^{\mathbf{m}}$ 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 difference between the realization $y_{i,t}$ and the forecasts ($\widehat{e}_{i,t}^{\mathbf{m}} = y_t - \widehat{y}_{i,t}^{\mathbf{m}}$). Similarly, $\widehat{y}_{i,t}^{\mathbf{AR}}$ is the pure AR-forecast and $\widehat{e}_{i,t}^{\mathbf{AR}}$ 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

[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.

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

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 by complicated, particularly when models under investigation are nested (see West, 1996). In our setting, 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

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

The test statistic is

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

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 $\widehat{y}_t^{direct}$ is said to be conditional efficient with respect to the production-side forecast $\widehat{y}_t^{supply}$ and the demand-side forecast $\widehat{y}_t^{demand}$ for each forecast combination scheme $\mathbf{m}$ if

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

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:

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

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 as well as the shrinked weights performed poorly at the early forecast stages. Later, when more information is available, they show quite satisfactory results.[28] MMA 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 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 now-

[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.

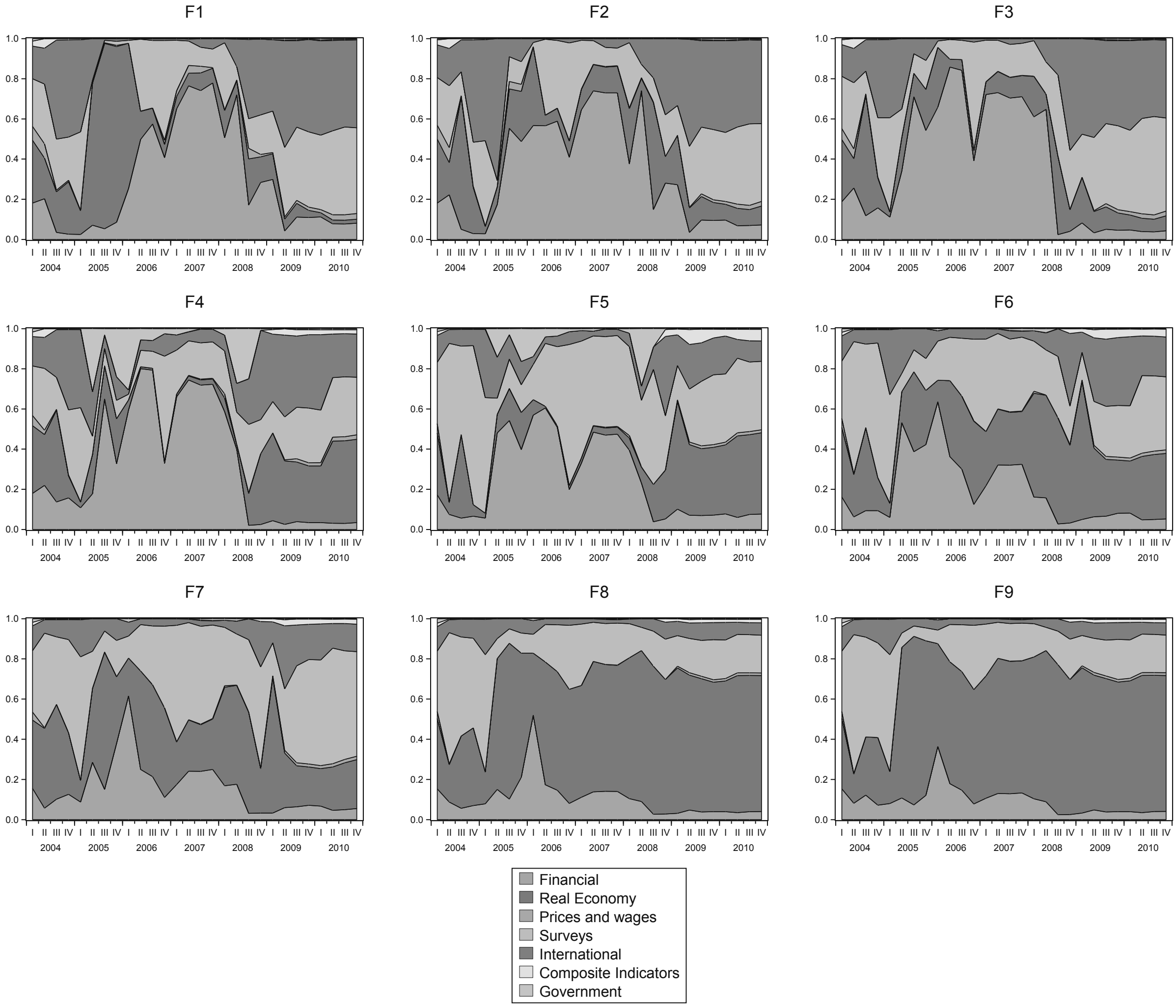
cast) accuracy (Stock and Watson, 2004; Timmermann, 2006). In particular we can support the findings of Kuzin *et al.* (2009) that pooling becomes even more important under mixed data frequencies. Rank-based weights offer consistent smaller forecast errors than any other (and more complicated) procedure. 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, 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.

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).

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 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.

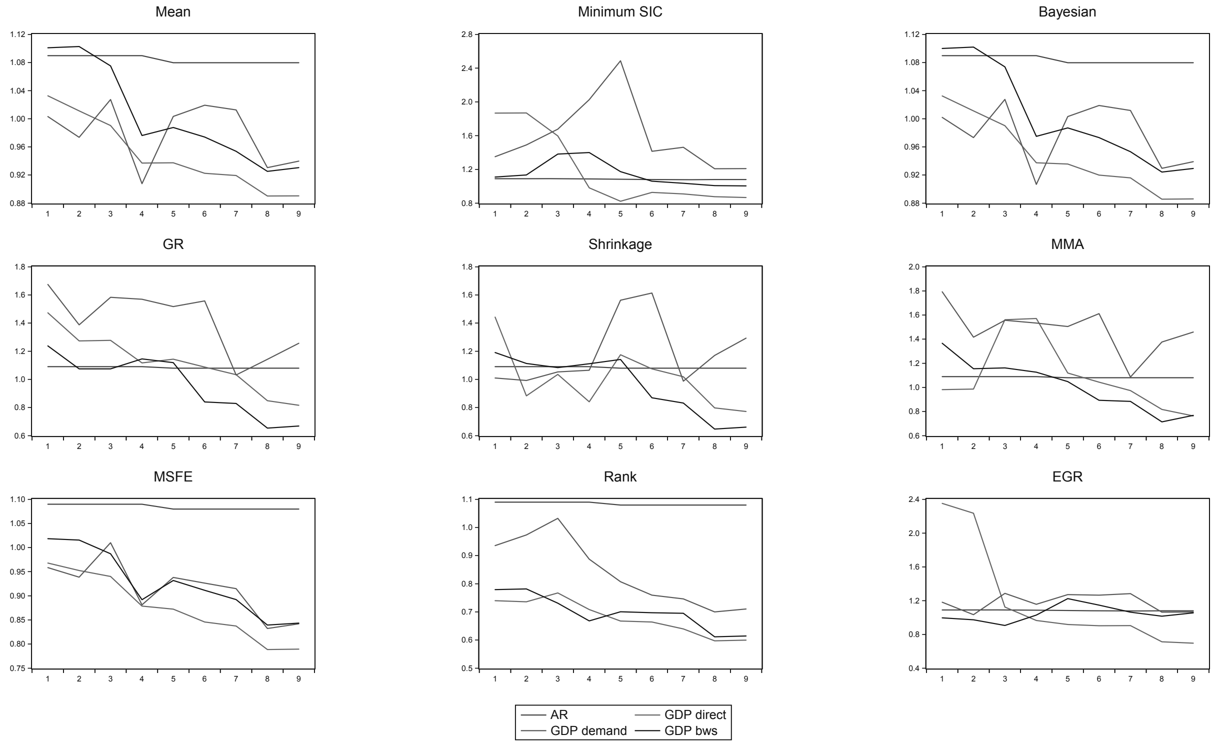
Figure 4 plots the RMSFE for the three forecasting methods along with the RMSFE of the univariate direct AR forecast depending on the forecast combination schemes and for different forecasting rounds. This makes it also possible to compare the performance across different pooling techniques. As expected, the rank-based scheme shows the best forecasting performance (mostly based on the direct approach). Also for msfe weights, the direct approach is the best. 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

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		1.105		1.102		1.045		1.056	
gva	1.066	1.098	1.091	1.133	1.086	1.047	1.042	1.076	1.054	0.984	1.056	0.956	1.038	0.942	1.040	0.994	1.045	0.990
minSIC																		
demand	0.724		0.798		1.051		2.065*		3.027		1.526*		1.608*		1.379		1.396	
gva	0.594	0.822	0.607	0.761	0.866	0.825	1.427	0.691	1.428	0.472	1.145	0.750	1.138	0.708	1.150	0.834	1.160	0.831
bayesian																		
demand	0.971		0.963		1.038		0.967		1.072		1.108		1.105		1.050		1.060	
gva	1.065	1.098	1.090	1.132	1.085	1.045	1.040	1.076	1.055	0.984	1.058	0.955	1.040	0.942	1.044	0.994	1.049	0.990
gr																		
demand	1.137**		1.090*		1.239		1.406		1.327*		1.433		0.998		1.347		1.541	
gva	0.840	0.739	0.844	0.774	0.841	0.679	1.026	0.730	0.978	0.737	0.772	0.539	0.802	0.804	0.771	0.572	0.820	0.532
shrink																		
demand	0.700		1.123		1.017		1.267**		1.330		1.502		0.969		1.467		1.675	
gva	0.825	1.179	1.261	1.122	1.047	1.029	1.321	1.043	0.971	0.730	0.809*	0.539*	0.817	0.843	0.811*	0.553*	0.856	0.511
MMA																		
demand	0.954		1.005		1.180		1.063		1.314		1.430		1.029		1.380		1.554	
gva	0.855	0.896	0.871	0.867	0.813	0.689	0.928	0.873	1.010	0.769	0.762*	0.533*	0.785	0.763	0.784	0.568	0.816	0.526
MFSE																		
demand	0.990		0.986		1.075		1.003		1.076		1.095		1.092		1.055		1.067	
gva	1.052	1.063	1.066	1.082	1.050	0.977	1.015	1.012	1.068	0.993	1.078	0.984	1.065	0.975	1.064	1.009	1.068	1.002
rank																		
demand	1.265*		1.323*		1.345*		1.252		1.209		1.144		1.167		1.172		1.184	
gva	1.053	0.833	1.062	0.803	0.952*	0.708*	0.943*	0.753*	1.050	0.868	1.050	0.918	1.087	0.931	1.024	0.874	1.024	0.865
egr																		
demand	0.502		0.462		1.143		1.198		1.386*		1.401*		1.418		1.493*		1.530*	
gva	0.423	0.843	0.435	0.941	0.806**	0.705**	1.065	0.889	1.333	0.962	1.272	0.908	1.174	0.828	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.

Figure 4: RMSFE over forecast rounds



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

line). However, due to the fact that the rank-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).

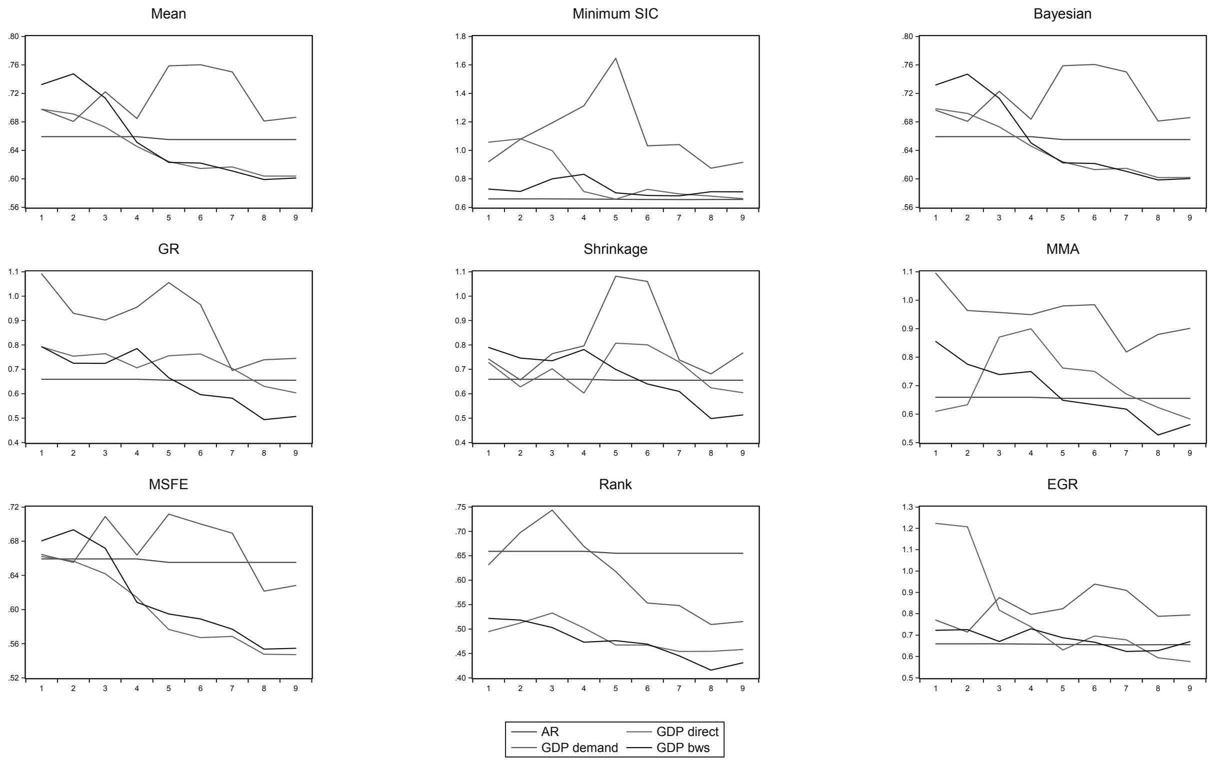
Table 3: Forecast encompassing tests

	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.

5 Robustness Analysis

Figure 5: MAFE over forecast rounds



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

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 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 procedure 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
direct GDP forecast									
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
demand-side GDP forecast									
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
production-side GDP forecast									
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 prediction. 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 is 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.

Given the different choices of model combination schemes, we find a clear winner for the application of MIDAS models: combination weights based on ranks computed from the models past performance. Our 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.

References

Andreou, E., Ghysels, E. and Kourtellos, A. (2010). 'Should macroeconomic forecasters use daily financial data and how?', Working Paper Series 42/10, Rimini Centre for Economic Analysis.

Andreou, E., Ghysels, E. and Kourtellos, A. (2011). 'Forecasting with mixed-frequency data', in M. P. Clemens and D. F. Hendry (eds), *Oxford Handbook of Economic Forecasting*, Oxford University Press.

Angelini, E., Camba-Mendez, G., Giannone, D. *et al.* (2011). 'Short-term forecasts of euro area GDP growth', *Econometrics Journal*, Vol. 14, pp. C25–C44.

Aruoba, S. B. and Diebold, F. X. (2010). 'Real-time macroeconomic monitoring: Real activity, inflation, and interactions.', *American Economic Review*, Vol. 100, pp. 20–24.

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

Banbura, M. and Rünstler, G. (2011). 'A look into the factor model black box: Publication lags and the role of hard and soft data in forecasting GDP', *International Journal of Forecasting*, Vol. 27, pp. 333–346.

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

Banbura, M., Giannone, D. and Reichlin, L. (2011). 'Nowcasting', in M. P. Clements and D. F. Hendry (eds), *The Oxford Handbook of Economic Forecasting*, Oxford University Press.

Banerjee, A., Marcellino, M. and Masten, I. (2005). 'Leading indicators for euro-area inflation and GDP growth', *Oxford Bulletin of Economics and Statistics*, Vol. 67, pp. 785–813.

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

Barhoumi, K., Darné, O., Ferrara, L. *et al.* (2011). 'Monthly GDP forecasting using bridge models: Application for the French economy', *Bulletin of Economic Research*, p. forthcoming.

Bates, J. M. and Granger, C. W. J. (1969). 'The combination of forecasts', *Operations Research Quarterly*, Vol. 20, pp. 451–468.

Burnham, K. P. and Anderson, D. R. (2004). 'Multimodel inference – understanding AIC and BIC in model selection', *Sociological Methods & Research*, Vol. 33, pp. 261–304.

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

Clements, M. P. (2004). *Evaluating Econometric Forecasts of Economic and Financial Variables*, Palgrave Macmillan.

Clements, M. P. and Hendry, D. F. (2011). 'Forecasting from mis-specified models in the presence of unanticipated location shifts', in M. P. Clements and D. F. Hendry (eds), *The Oxford Handbook of Economic Forecasting*, Oxford University Press.

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

Cristadoro, R., Forni, M., Reichlin, L. *et al.* (2005). 'A core inflation indicator for the euro area', *Journal of Money, Credit and Banking*, Vol. 37, pp. 539–60.

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

Drechsel, K. and Maurin, L. (2011). 'Flow on conjunctural information and forecast of euro area economic activity', *Journal of Forecasting*, Vol. 30, p. 336354.

Drechsel, K. and Scheufele, R. (2012a). 'The financial crisis from a forecaster's perspective', *Kredit und Kapital*, Vol. 2012, pp. 1–26.

Drechsel, K. and Scheufele, R. (2012b). 'The performance of short-term forecasts of the german economy before and during the 2008/2009 recession', *International Journal of Forecasting*, Vol. 28, pp. 428 – 445.

Eurostat (2008). 'Metadata: Statistical classification of economic activities in the european community, rev. 1.1 (2002)', `http://ec.europa.eu/eurostat/ramon`.

Fair, R. C. and Shiller, R. J. (1990). 'Comparing information in forecasts from econometric models', *American Economic Review*, Vol. 80, pp. 375–389.

Faust, J., Gilchrist, S., Wright, J. H. *et al.* (2011). 'Credit spreads as predictors of real-time economic activity: A bayesian model-averaging approach', NBER Working Papers 16725, National Bureau of Economic Research, Inc.

Figlewski, S. (1983). 'Optimal price forecasting using survey data', *The Review of Economics and Statistics*, Vol. 65, pp. 13–21.

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

Giacomini, R. and Komunjer, I. (2005). 'Evaluation and combination of conditional quantile forecasts', *Journal of Business & Economic Statistics*, Vol. 23, pp. 416–431.

Giacomini, R. and White, H. (2006). 'Tests of conditional predictive ability', *Econometrica*, Vol. 74, pp. 1545–1578.

Giannone, D., Reichlin, L. and Small, D. (2008). 'Nowcasting: The real-time informational content of macroeconomic data', *Journal of Monetary Economics*, Vol. 55, pp. 665–676.

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

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

Granger, C. W. and Ramanathan, R. (1984). 'Improved methods of combining forecasting', *Journal of Forecasting*, Vol. 3, pp. 197–204.

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

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

Hansen, B. E. (2007). 'Least squares model averaging', *Econometrica*, Vol. 75, pp. 1175–1189.

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

Harvey, D. I., Leybourne, S. J. and Newbold, P. (1998). 'Tests for forecast encompassing', *Journal of Business & Economic Statistics*, Vol. 16, pp. 254–259.

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

Hendry, D. F. and Hubrich, K. (2011). 'Combining disaggregate forecasts or combining disaggregate information to forecast an aggregate', *Journal of Business & Economic Statistics*, Vol. 29, pp. 216–227.

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

Judge, G. G., Griffiths, W. E., Hill, R. C. *et al.* (1985). *The Theory and Practice of Econometrics*, John Wiley and Sons, 2nd edition ed.

Kapetanios, G., Labhard, V. and Price, S. (2008). 'Forecasting using bayesian and information-theoretic model averaging: An application to U.K. inflation', *Journal of Business & Economic Statistics*, Vol. 26, pp. 33–41.

Kitchen, J. and Monaco, R. (2003). 'Real-time forecasting in practice', *Business Economics*, Vol. 38, pp. 10–19.

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

Ledoit, O. and Wolf, M. (2003). 'Improved estimation of the covariance matrix of stock returns with an application to portfolio selection', *Journal of Empirical Finance*, Vol. 10, pp. 603–621.

Lütkepohl, H. (1984). 'Forecasting contemporanously aggregated vector ARMA processess', *Journal of Business & Economic Statistics*, Vol. 2, pp. 201–214.

Mallows, C. L. (1973). 'Some comments on CP', *Technometrics*, Vol. 15, pp. 661–675.

Marcellino, M. and Schumacher, C. (2010). 'Factor MIDAS for nowcasting and forecasting with ragged-edge data: A model comparison for german GDP', *Oxford Bulletin of Economics and Statistics*, Vol. 72, pp. 518–550.

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

Parigi, G. and Schlitzer, G. (1995). 'Quarterly forecasts of the italian business cycle by means of monthly economic indicators', *Journal of Forecasting*, Vol. 14, p. 117141.

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

Stock, J. H. and Watson, M. W. (2003). 'Forecasting output and inflation: The role of asset prices', *Journal of Economic Literature*, Vol. 47, pp. 788–829.

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

Stock, J. H. and Watson, M. W. (2006). 'Forecasting with many predictors', in G. Elliot, C. W. Granger and A. Timmermann (eds), *Handbook of Forecasting*, Vol. 1, Elsevier.

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

Timmermann, A. (2006). 'Forecast combinations', in G. Elliot, C. W. Granger and A. Timmermann (eds), *Handbook of Forecasting*, Vol. 1, Elsevier.

West, K. D. (1996). 'Inference about predictive ability', *Econometrica*, Vol. 64, pp. 1067–1084.

Wright, J. H. (2008). 'Bayesian model averaging and exchange rate forecasts', *Journal of Econometrics*, Vol. 146, pp. 329–341.

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

Table 5: Set of Indicators

Label	Name	Months of Publication Lags	Frequency
GDP	GDP		q
CNPER	consumer expenditure		q
EXNGS	exports of goods & services		q
IMNGS	imports of goods & services		q
EAGCTCE	gross fixed capital formation		q
CNGOV	government consumption		q
GCCON	construction investment		q
IAUS	capital investments		q
IVOR	inventories		q
GVAAFFD	gva - agriculture, forestry & fishing		q
GVACOND	gva - construction		q
GVAFIND	gva - financing,renting & corporate services		q
GVAINDD	gva - producing sector excl. construction		q
PAVMSCD	gva - value added - manufacturing sector		q
GVAOTHD	gva - public & private service suppliers		q
GVATRAD	gva - wholesale & retail trade & transport		q
GVATOTD	gva - total		q
GVADIFF	diff = gva -bip		q
Finance			
PQ3197A	lending to enterprises & self employed: housing loans	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 indl.countr,CPI-basis	1	m
SHRPRCF	DAX share price index	0	m
BDINECE	nominal effective exchange rate	0	m
VDAXNEW	VDAX-new volatility index - price index	0	m
VDAXIDX	VDAX volatility index (old) - price index	0	m
MLNF2AE	corporate non-financial aa (euro)	0	m
MLNF3BE	non-financial bbb	0	m
MLNP3BE	financial bbb (euro)	0	m
MLHEUCU	high yield (euro)	0	m
TSD304B	overnight deposits - m1	1	m
M2C	money supply - m2	1	m
M3C	money supply - m3	1	m
EMECBM1	em money supply: m1 (ep)	1	m
EMECBM1FB	em money supply: m1 (flows)	1	m
EMEBM2	em money supply: m2-m1 (index)	1	m
EMEBM2F1B	em money supply: m2-m1 (flows)	1	m
EMEBM3	em money supply: m3-m2 (ep)	1	m
EMEBM3F2B	em money supply: m3-m2 (flows)	1	m
OU0123A	bank lending to domestic non-banks - short term	1.5	m
OU0175A	bank lending to 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
USNA05G	IP - manufacturing: capital goods	1.5	m
USNA06G	IP - manufacturing: consumer durables	1.5	m

To be continued...

Label	Name	Months of Publication Lags	Frequency
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
STFEXEG	ind.t/o: energy exc.elec., gas, steam&hot water supply, fgn.	1.5	m
STDMANG	ind.t/o: manufacturing, dom.	1.5	m
STFMANG	ind.t/o: manufacturing, fgn.	1.5	m
STDVEMG	ind.t/o: motor veh., trailers&semi-trail., dom.	1.5	m
STFVEMG	ind.t/o: motor veh., trailers&semi-trail., fgn.	1.5	m
STDCEOG	ind.t/o: computer, electronic & optical products, dom.	1.5	m
STFCEOG	ind.t/o: computer, electronic & optical products, fgn.	1.5	m
STDCHNG	ind.t/o: chemicals & chemical products, dom.	1.5	m
STFCHNG	ind.t/o: chemicals & chemical products, fgn.	1.5	m
STDMYEG	ind. t/o: machinery & equip. n.e.c., dom.	1.5	m
STFMYEG	ind. t/o: machinery & equip. n.e.c., fgn.	1.5	m
WTEXMOG	wholesale trade excluding motor vehicles	1.5	m
WHTCFWH	wholesale trade - clothing & footwear	1.5	m
WHTCHEH	wholesale trade - chemical products	1.5	m
WHTCNMH	wholesale trade - construction machinery	1.5	m
WHTSLGH	wholesale trade - solid, liquid & gaseous fuels & related prods	1.5	m
XSC500D	exports (volume on basis2005)	1.5	m
XSC501D	imports (volume on basis2005)	1.5	m
NEWORDG	manufacturing orders	1.5	m
USC001G	new orders to manufacturing	1.5	m
BPRORDG	new orders to manufacturing - intermediate goods	1.5	m
CAPORDG	new orders to manufacturing - capital goods	1.5	m
CONORDG	new orders to manufacturing - consumer goods	1.5	m
DOMORDG	new orders to manufacturing - domestic	1.5	m
DBPORDG	new orders to manufacturing - domestic: intermediate goods	1.5	m
DCPORDG	new orders to manufacturing - domestic: capital goods	1.5	m
DCNORDG	new orders to manufacturing - domestic: consumer goods	1.5	m
OVRORDG	new orders to manufacturing - from abroad	1.5	m
OBPORDG	new orders to manufacturing - from abroad: intermediate goods	1.5	m
OCPORDG	new orders to manufacturing - from abroad: capital goods	1.5	m
OCNORDG	new orders to manufacturing - from abroad: consumer goods	1.5	m
USC509G	mfg orders: machinery & equipment nec, dom.	1.5	m
USC510G	mfg orders: machinery & equipment nec, fgn.	1.5	m
USC659G	mfg orders: motor vehicles, trailers, semi-trailers, dom.	1.5	m
USC660G	mfg orders: motor vehicles, trailers, semi-trailers, fgn.	1.5	m
USC587G	mfg orders: computer, elecc.&opt.prds., elecl. equip., dom.	1.5	m
USC588G	mfg orders: computer, elecc.&opt.prds., elecl. equip., fgn	1.5	m
USC203G	mfg orders: chem.&chem.prds., basic pharm.prds.&prepar., dom.	1.5	m
USC204G	mfg orders: chem.&chem.prds., basic pharm.prds.&prepar., fgn	1.5	m
USDA16G	construction orders received	1.5	m
USMB28B	turnover in construction- total	1.5	m
USMB01B	employment in construction	1.5	m
HOUSINP	housing permits issued for bldg.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-indl. cnstr.	2	m
WGUS01LAB	bldg.permits granted: all bldg.	2	m
HOURCON	hours worked	2	m
RVN	new registrations - all vehicles voln	0.5	m
RVNCARP	new registrations - cars voln	0.5	m
RVNTRUP	new registrations - heavy trucks voln	0	m

To be continued...

Label	Name	Months of Publication Lags	Frequency
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
ESEITHT	hours worked: industry (excluding construction)	1.5	m
VACTOTO	vacancies	0	m
Prices and Wages			
CONPRCE	CPI	0	m
USFB76E	CPI (excluding energy)	0.5	m
HWWAINF	HWWA index	0.5	m
IUW510F	HWWA index, energy	0.5	m
IUW501F	HWWA index, excl. energy	0.5	m
EMEBPOILA	oil prices (euros per barrel)	0	m
UKOILBREN	UK avg. brent oil price	0	m
SAERFRLI	London gold price - US $	0	m
USZI01E	import price index	1	m
USZJ01E	export price index	1	m
WH75	wholesale output price index rebased to 1975=100	0.5	m
PRODPRE	PPI	0.5	m
Survey Indicators			
WDIFCLIMR	Economic climate - world	0.5	q
WDIFEXPER	Economic expectations - world	0.5	q
IFDMT	mfg.: capacity utilization	0.5	q
ZEWST	ZEW present economic situation	0	m
ZEWECSR	ZEW indicator of economic sentiment	0	m
CNFBUSQ	ifo business climate index (pan Germany)	0	m
IFOEXPQ	business expectations	0	m
IFOBUSQ	assessment of business situation	0	m
IFOMTLQ	business climate index: manufacturing	0	m
IFOMTKQ	business expectations: manufacturing	0	m
IFOMTAQ	assessment of business situation: manufacturing	0	m
IFDMTJQ	mfg.: exports expected next 3 mth	0	m
IFDMTMQ	mfg.: foreign orders on hand	0	m
IFDMTCQ	mfg.: inventory of finished goods	0	m
IFDMTFQ	mfg.: orders on hand	0	m
IFOMCAQ	assessment of business situation: mfg. - consumer goods	0	m
IFOMCLQ	business climate index: 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
IFOBDQQ	business climate index: construction	0	m
IFOBDPQ	business expectations: construction	0	m
IFDCTIQ	cnstr.ind.: assessment of orders on hand	0	m
IFPCTWQ	cnstr.ind.: 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
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

To be continued...

Label	Name	Months of Publication Lags	Frequency
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
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**
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**

To be continued. . .

	F1	F2	F3	F4	F5	F6	F7	F8	F9
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
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

To be continued...

	F1	F2	F3	F4	F5	F6	F7	F8	F9
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
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 *

To be continued. . .

	F1	F2	F3	F4	F5	F6	F7	F8	F9
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
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

To be continued...

	F1	F2	F3	F4	F5	F6	F7	F8	F9
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).

Swiss National Bank Working Papers published since 2004:

2004-1 Samuel Reynard: Financial Market Participation and the Apparent Instability of Money Demand

2004-2 Urs W. Birchler and Diana Hancock: What Does the Yield on Subordinated Bank Debt Measure?

2005-1 Hasan Bakhshi, Hashmat Khan and Barbara Rudolf: The Phillips curve under state-dependent pricing

2005-2 Andreas M. Fischer: On the Inadequacy of Newswire Reports for Empirical Research on Foreign Exchange Interventions

2006-1 Andreas M. Fischer: Measuring Income Elasticity for Swiss Money Demand: What do the Cantons say about Financial Innovation?

2006-2 Charlotte Christiansen and Angelo Ranaldo: Realized Bond-Stock Correlation: Macroeconomic Announcement Effects

2006-3 Martin Brown and Christian Zehnder: Credit Reporting, Relationship Banking, and Loan Repayment

2006-4 Hansjörg Lehmann and Michael Manz: The Exposure of Swiss Banks to Macroeconomic Shocks – an Empirical Investigation

2006-5 Katrin Assenmacher-Wesche and Stefan Gerlach: Money Growth, Output Gaps and Inflation at Low and High Frequency: Spectral Estimates for Switzerland

2006-6 Marlene Amstad and Andreas M. Fischer: Time-Varying Pass-Through from Import Prices to Consumer Prices: Evidence from an Event Study with Real-Time Data

2006-7 Samuel Reynard: Money and the Great Disinflation

2006-8 Urs W. Birchler and Matteo Facchinetti: Can bank supervisors rely on market data? A critical assessment from a Swiss perspective

2006-9 Petra Gerlach-Kristen: A Two-Pillar Phillips Curve for Switzerland

2006-10 Kevin J. Fox and Mathias Zurlinden: On Understanding Sources of Growth and Output Gaps for Switzerland

2006-11 Angelo Ranaldo: Intraday Market Dynamics Around Public Information Arrivals

2007-1 Andreas M. Fischer, Gulzina Isakova and Ulan Termechikov: Do FX traders in Bishkek have similar perceptions to their London colleagues? Survey evidence of market practitioners' views

2007-2 Ibrahim Chowdhury and Andreas Schabert: Federal Reserve Policy viewed through a Money Supply Lens

2007-3 Angelo Ranaldo: Segmentation and Time-of-Day Patterns in Foreign Exchange Markets

2007-4 Jürg M. Blum: Why 'Basel II' May Need a Leverage Ratio Restriction

2007-5 Samuel Reynard: Maintaining Low Inflation: Money, Interest Rates, and Policy Stance

2007-6 Rina Rosenblatt-Wisch: Loss Aversion in Aggregate Macroeconomic Time Series

2007-7 Martin Brown, Maria Rueda Maurer, Tamara Pak and Nurlanbek Tynaev: Banking Sector Reform and Interest Rates in Transition Economies: Bank-Level Evidence from Kyrgyzstan

2007-8 Hans-Jürg Büttler: An Orthogonal Polynomial Approach to Estimate the Term Structure of Interest Rates

2007-9 Raphael Auer: The Colonial Origins Of Comparative Development: Comment. A Solution to the Settler Mortality Debate

2007-10 Franziska Bignasca and Enzo Rossi: Applying the Hirose-Kamada filter to Swiss data: Output gap and exchange rate pass-through estimates

2007-11 Angelo Ranaldo and Enzo Rossi: The reaction of asset markets to Swiss National Bank communication

2007-12 Lukas Burkhard and Andreas M. Fischer: Communicating Policy Options at the Zero Bound

2007-13 Katrin Assenmacher-Wesche, Stefan Gerlach, and Toshitaka Sekine: Monetary Factors and Inflation in Japan

2007-14 Jean-Marc Natal and Nicolas Stoffels: Globalization, markups and the natural rate of interest

2007-15 Martin Brown, Tullio Jappelli and Marco Pagano: Information Sharing and Credit: Firm-Level Evidence from Transition Countries

2007-16 Andreas M. Fischer, Matthias Lutz and Manuel Wälti: Who Prices Locally? Survey Evidence of Swiss Exporters

2007-17 Angelo Ranaldo and Paul Söderlind: Safe Haven Currencies

2008-1 Martin Brown and Christian Zehnder: The Emergence of Information Sharing in Credit Markets

2008-2 Yvan Lengwiler and Carlos Lenz: Intelligible Factors for the Yield Curve

2008-3 Katrin Assenmacher-Wesche and M. Hashem Pesaran: Forecasting the Swiss Economy Using VECX* Models: An Exercise in Forecast Combination Across Models and Observation Windows

2008-4 Maria Clara Rueda Maurer: Foreign bank entry, institutional development and credit access: firm-level evidence from 22 transition countries

2008-5 Marlene Amstad and Andreas M. Fischer: Are Weekly Inflation Forecasts Informative?

2008-6 Raphael Auer and Thomas Chaney: Cost Pass Through in a Competitive Model of Pricing-to-Market

2008-7 Martin Brown, Armin Falk and Ernst Fehr: Competition and Relational Contracts: The Role of Unemployment as a Disciplinary Device

2008-8 Raphael Auer: The Colonial and Geographic Origins of Comparative Development

2008-9 Andreas M. Fischer and Angelo Ranaldo: Does FOMC News Increase Global FX Trading?

2008-10 Charlotte Christiansen and Angelo Ranaldo: Extreme Coexceedances in New EU Member States' Stock Markets

2008-11 Barbara Rudolf and Mathias Zurlinden: Measuring capital stocks and capital services in Switzerland

2008-12 Philip Sauré: How to Use Industrial Policy to Sustain Trade Agreements

2008-13 Thomas Bolli and Mathias Zurlinden: Measuring growth of labour quality and the quality-adjusted unemployment rate in Switzerland

2008-14 Samuel Reynard: What Drives the Swiss Franc?

2008-15 Daniel Kaufmann: Price-Setting Behaviour in Switzerland – Evidence from CPI Micro Data

2008-16 Katrin Assenmacher-Wesche and Stefan Gerlach: Financial Structure and the Impact of Monetary Policy on Asset Prices

2008-17 Ernst Fehr, Martin Brown and Christian Zehnder: On Reputation: A Microfoundation of Contract Enforcement and Price Rigidity

2008-18 Raphael Auer and Andreas M. Fischer: The Effect of Low-Wage Import Competition on U.S. Inflationary Pressure

2008-19 Christian Beer, Steven Ongena and Marcel Peter: Borrowing in Foreign Currency: Austrian Households as Carry Traders

2009-1 Thomas Bolli and Mathias Zurlinden: Measurement of labor quality growth caused by unobservable characteristics

2009-2 Martin Brown, Steven Ongena and Pinar Yeşin: Foreign Currency Borrowing by Small Firms

2009-3 Matteo Bonato, Massimiliano Caporin and Angelo Ranaldo: Forecasting realized (co)variances with a block structure Wishart autoregressive model

2009-4 Paul Söderlind: Inflation Risk Premia and Survey Evidence on Macroeconomic Uncertainty

2009-5 Christian Hott: Explaining House Price Fluctuations

2009-6 Sarah M. Lein and Eva Köberl: Capacity Utilisation, Constraints and Price Adjustments under the Microscope

2009-7 Philipp Haene and Andy Sturm: Optimal Central Counterparty Risk Management

2009-8 Christian Hott: Banks and Real Estate Prices

2009-9 Terhi Jokipii and Alistair Milne: Bank Capital Buffer and Risk Adjustment Decisions

2009-10 Philip Sauré: Bounded Love of Variety and Patterns of Trade

2009-11 Nicole Allenspach: Banking and Transparency: Is More Information Always Better?

2009-12 Philip Sauré and Hosny Zoabi: Effects of Trade on Female Labor Force Participation

2009-13 Barbara Rudolf and Mathias Zurlinden: Productivity and economic growth in Switzerland 1991-2005

2009-14 Sébastien Kraenzlin and Martin Schlegel: Bidding Behavior in the SNB's Repo Auctions

2009-15 Martin Schlegel and Sébastien Kraenzlin: Demand for Reserves and the Central Bank's Management of Interest Rates

2009-16 Carlos Lenz and Marcel Savioz: Monetary determinants of the Swiss franc

2010-1 Charlotte Christiansen, Angelo Ranaldo and Paul Söderlind: The Time-Varying Systematic Risk of Carry Trade Strategies

2010-2 Daniel Kaufmann: The Timing of Price Changes and the Role of Heterogeneity

2010-3 Loriano Mancini, Angelo Ranaldo and Jan Wrampelmeyer: Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums

2010-4 Samuel Reynard and Andreas Schabert: Modeling Monetary Policy

2010-5 Pierre Monnin and Terhi Jokipii: The Impact of Banking Sector Stability on the Real Economy

2010-6 Sébastien Kraenzlin and Thomas Nellen: Daytime is money

2010-7 Philip Sauré: Overreporting Oil Reserves

2010-8 Elizabeth Steiner: Estimating a stock-flow model for the Swiss housing market

2010-9 Martin Brown, Steven Ongena, Alexander Popov, and Pinar Yeşin: Who Needs Credit and Who Gets Credit in Eastern Europe?

2010-10 Jean-Pierre Danthine and André Kurmann: The Business Cycle Implications of Reciprocity in Labor Relations

2010-11 Thomas Nitschka: Momentum in stock market returns: Implications for risk premia on foreign currencies

2010-12 Petra Gerlach-Kristen and Barbara Rudolf: Macroeconomic and interest rate volatility under alternative monetary operating procedures

2010-13 Raphael Auer: Consumer Heterogeneity and the Impact of Trade Liberalization: How Representative is the Representative Agent Framework?

2010-14 Tommaso Mancini Griffoli and Angelo Ranaldo: Limits to arbitrage during the crisis: funding liquidity constraints and covered interest parity

2010-15 Jean-Marc Natal: Monetary Policy Response to Oil Price Shocks

2010-16 Kathrin Degen and Andreas M. Fischer: Immigration and Swiss House Prices

2010-17 Andreas M. Fischer: Immigration and large banknotes

2010-18 Raphael Auer: Are Imports from Rich Nations Deskilling Emerging Economies? Human Capital and the Dynamic Effects of Trade

2010-19 Jean-Pierre Danthine and John B. Donaldson: Executive Compensation: A General Equilibrium Perspective

2011-1 Thorsten Beck and Martin Brown: Which Households Use Banks? Evidence from the Transition Economies

2011-2 Martin Brown, Karolin Kirschenmann and Steven Ongena: Foreign Currency Loans – Demand or Supply Driven?

2011-3 Victoria Galsband and Thomas Nitschka: Foreign currency returns and systematic risks

2011-4 Francis Breedon and Angelo Ranaldo: Intraday patterns in FX returns and order flow

2011-5 Basil Guggenheim, Sébastien Kraenzlin and Silvio Schumacher: Exploring an uncharted market: Evidence on the unsecured Swiss franc money market

2011-6 Pamela Hall: Is there any evidence of a Greenspan put?

2011-7 Daniel Kaufmann and Sarah Lein: Sectoral Inflation Dynamics, Idiosyncratic Shocks and Monetary Policy

2011-8 Iva Cecchin: Mortgage Rate Pass-Through in Switzerland

2011-9 Raphael A. Auer, Kathrin Degen and Andreas M. Fischer: Low-Wage Import Competition, Inflationary Pressure, and Industry Dynamics in Europe

2011-10 Raphael A. Auer and Philip Sauré: Spatial Competition in Quality, Demand-Induced Innovation, and Schumpeterian Growth

2011-11 Massimiliano Caporin , Angelo Ranaldo and Paolo Santucci de Magistris: On the Predictability of Stock Prices: a Case for High and Low Prices

2011-12 Jürg Mägerle and Thomas Nellen: Interoperability between central counterparties

2011-13 Sylvia Kaufmann: K-state switching models with endogenous transition distributions

2011-14 Sébastien Kraenzlin and Benedikt von Scarpatetti: Bargaining Power in the Repo Market

2012-01 Raphael A. Auer: Exchange Rate Pass-Through, Domestic Competition, and Inflation: Evidence from the 2005/08 Revaluation of the Renminbi

2012-02 Signe Krogstrup, Samuel Reynard and Barbara Sutter: Liquidity Effects of Quantitative Easing on Long-Term Interest Rates

2012-03 Matteo Bonato, Massimiliano Caporin and Angelo Ranaldo: Risk spillovers in international equity portfolios

2012-04 Thomas Nitschka: Banking sectors' international interconnectedness: Implications for consumption risk sharing in Europe

2012-05 Martin Brown, Steven Ongena and Pinar Yeşin: Information Asymmetry and Foreign Currency Borrowing by Small Firms

2012-06 Philip Sauré and Hosny Zoabi: Retirement Age across Countries: The Role of Occupations

2012-07 Christian Hott and Terhi Jokipii: Housing Bubbles and Interest Rates

2012-08 Romain Baeriswyl and Camille Cornand: Reducing overreaction to central bank's disclosures: theory and experiment

2012-09 Bo E. Honoré, Daniel Kaufmann and Sarah Lein: Asymmetries in Price-Setting Behavior: New Microeconometric Evidence from Switzerland

2012-10 Thomas Nitschka: Global and country-specific business cycle risk in time-varying excess returns on asset markets

2012-11 Raphael A. Auer, Thomas Chaney and Philip Sauré: Quality Pricing-to-Market

2012-12 Sébastien Kraenzlin and Thomas Nellen: Access policy and money market segmentation

2012-13 Andreas Kropf and Philip Sauré: Fixed Costs per Shipment

2012-14 Raphael A. Auer and Raphael S. Schoenle: Market Structure and Exchange Rate Pass-Through

2012-15 Raphael A. Auer: What Drives Target2 Balances? Evidence From a Panel Analysis

2012-16 Katja Drechsel and Rolf Scheufele: Bottom-up or Direct? Forecasting German GDP in a Data-rich Environment

Swiss National Bank Working Papers are also available at www.snb.ch, section Publications/Research
Subscriptions or individual issues can be ordered at Swiss National Bank, Fraumünsterstrasse 8, CH-8022 Zurich,
fax +41 44 631 81 14, E-mail library@snb.ch