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Nowcasting German GDP: A comparison of bridge and factor models

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Abstract

Governments and central banks need to have an accurate and timely assessment of gross domestic product's (GDP) growth rate for the current quarter, as this is essential for providing a reliable and early analysis of the current economic situation. This paper presents a series of models conceived to forecast the current German GDP's quarterly growth rate. These models are designed to be used on a monthly basis by integrating monthly economic information through bridge models, thus allowing for the economic interpretation of the data. We do also forecast German GDP by dynamic factor models. The combination of these two approaches allows selecting economically relevant explanatory variables among a large data set of hard and soft data. In addition, a rolling forecast study is carried out to assess the forecasting performance of the estimated models. To this end, publication lags are taken into account in order to run pseudo out-of-sample forecasts. We show that it is possible to get reasonably good estimates of current quarterly GDP growth in anticipation of the official release, especially from bridge models.

JEL classification: C52; C53; E20

Keywords: GDP forecasting; Bridge models; Factor models

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1. Introduction

Policy-makers and analysts are continually assessing the state of the economy. Governments and central banks need to have an accurate and timely assessment of gross domestic product (GDP) growth rates for the current quarter in order to provide for a reliable and early analysis of the ongoing economic situation. The accuracy of such forecasts can thus have important repercussions on the policy measures taken. GDP is, however, only available on a quarterly basis. In addition, first official estimations are only published after a time span of 2 or 3 months (around 45 days after the end of the reference quarter for the main European countries) and these first GDP estimations are often revised significantly. The aim of the present analysis is, therefore, to propose a number of models designed to forecast the current German quarterly GDP growth rates on a monthly basis and using a large set of monthly hard and soft data.[1]

Albeit their paramount importance for policy makers, forecast models of German GDP growth rates are scarce in the corresponding field of literature. Compared to other countries, German GDP growth rates exhibit more volatility, inducing higher forecast errors and, hence, making forecasts more difficult. This higher volatility might stem from Germany's specialization in the industrial sector (the production of services is smother as evolutions in investment and inventories play a smaller role) and its high sensitivity *vis-a-vis* the global business cycle (due to the importance of exports for German growth). The section on bridge models treats these two points in more detail.

Evolutions in Europe's biggest economy have necessarily repercussions on economic data for the euro zone, as Germany accounts for almost 30% of the euro area's aggregate output (versus 21% for France). In addition, the aforementioned volatility of German GDP affects euro area growth aggregates. In the third quarter of 2011, German GDP expanded by 2.6% y.o.y. accompanied by a increase in the euro area's GDP of 1.4% y.o.y. Without Germany's contribution this increase would have been less pronounced with 0.9% y.o.y. Timely and accurate forecasts of German GDP are, hence, also important for policy actions decided upon on a European level, for which monetary policy is the most prominent example.

To that end, we forecast German GDP growth rates for the current quarter by factor and bridge models, described in the following sections. Recently, factors models have emerged as an interesting tool for short-term forecasting of real activity. A series of recent papers by, among others, Stock and Watson (2002a, 2002b), Forni et al. (2004, 2005) or Giannone, Reichlin, and Small (2008) have put forward the advances in estimation techniques that allow improving the efficiency of dynamic factor models (DFM, henceforth). This type of model is particularly appealing as it can be applied to large data sets (e.g., Angelini, Camba-Mendez, Giannone, Reichlin, & Rünstler, 2011; Barhoumi, Darné, & Ferrara, 2010; Schumacher & Breitung, 2008; Schumacher, 2007). More precisely, DFMs allow summarizing the information contained in large datasets and extracting a few common factors that can then be employed to forecast output and its components.[2]

The DFMs are based on static and dynamic principal components. The static principal components are obtained as in Stock and Watson (2002a, 2002b). The dynamic principal components are based on either time domain methods, as in Doz, Giannone and Reichlin (2011, 2012), or frequency domain methods, as in Forni et al. (2004, 2005). To the best of our knowledge, Banerjee,

[1] A number of studies demonstrate the advantages of incorporating monthly data in forecasting GDP and other National Account components (e.g., Camacho & Perez-Quiros, 2010; Coutino, 2005; Ingenito & Trehan, 1996; Rünstler & Sédillot, 2003; Zheng & Rossiter, 2006).

[2] See Breitung and Eickmeier (2006), Stock and Watson (2006), Eickmeier and Ziegler (2008) for a discussion on factor models.

Marcellino, and Masten (2005) and Banerjee and Marcellino (2006) are the only studies that compare the forecasting performance of the automatically selected BMs and the DFMs – for Euro-area and US GDP growth, respectively. These studies, however, only use factor models *a la* Stock and Watson (2002a, 2002b), for which results are not conclusive in favor of one or the other. DFMs have so far rarely been used for forecasting German GDP growth rates; exceptions to this are Schumacher (2007) and Rünstler et al. (2009).[3] While the econometric performance of DFMs is very satisfactory, an important caveat of this approach is that the economic content of factors is difficult to interpret from an economic point of view. For that reason we complete this analysis by several bridge models which allow for a more straightforward interpretation of the data used.

In order to provide an economic interpretation for the forecasts, another often used alternative is to construct bridge models (BM, henceforth). These linear regressions "bridge", i.e. link monthly variables to quarterly GDP growth. Such models have been widely considered in the literature, and are especially used to forecast GDP growth in national and international institutions (e.g., Barhoumi, Darné, Ferrara, & Pluyaud, in press; Diron, 2008; Golinelli & Parigi, 2005; Parigi & Schlitzer, 1995; Rünstler & Sédillot, 2003; Sédillot & Pain, 2003; Zheng & Rossiter, 2006). To our knowledge, only Baffigi, Golinelli, and Parigi (2004) and Golinelli and Parigi (2007) have used BMs for forecasting German GDP growth.[4]

In the present analysis, we propose to compare the nowcasting performances of BMs and DFMs for German GDP growth rates.[5] In order to consider a large number of macroeconomic time series in the BMs, the variables are selected through an automatic selection procedure (Banerjee & Marcellino, 2006; Banerjee et al., 2005; Golinelli & Parigi, 2005). This procedure, called general-to-specific (Gets), was introduced by Hendry (1979), implemented in an automated way by Hoover and Perez (1999) and improved by Krolzig and Hendry (2001). Finally, the BMs are estimated using quarterly averages of monthly data as explanatory variables.

A second objective of this paper is to provide three monthly forecasting exercises of the German GDP growth rate for a given quarter. To this purpose, we use monthly hard and soft data selected depending on their publication dates, as the aim is to obtain as timely information as possible for the quarter of interest. Several studies report that soft data contain less information concerning real activity data than hard data (e.g., Baffigi et al., 2004; Banerjee et al., 2005; Forni, Hallin, Lippi, & Reichlin, 2003; Rünstler & Sédillot, 2003).[6] However, Giannone et al. (2008) and Banbura and Rünstler (2011) show that, once their publication lag is taken into account, real activity data are much less relevant, while surveys take their place. More precisely, business surveys offer some clear advantages over hard data: first of all, they provide for a signal that is obtained directly from economic actors and that reflects the short-term prospects of their proper

[3] Schumacher (2007) does not perform nowcasting for the German GDP growth rate.

[4] Another way to link a quarterly variable to monthly indicators is the mixed-data sampling framework (MIDAS) proposed by Ghysels, Sinko, and Valkanov (2007) and applied to German GDP in Marcellino and Schumacher (2008), Schumacher and Breitung (2008) and Kuzin, Marcellino, and Schumacher (2011). Clements and Galvão (2008) compare MIDAS and bridge equation approaches and find that the performance of MIDAS and bridge equations is comparable.

[5] For the Euro area see, e.g., Baffigi et al. (2004), Banerjee et al. (2005), Dreger and Marcellino (2007), Diron (2008), Ruth (2008), Hahn and Skudelny (2008).

[6] Exceptions to this general result are the studies by Giannone, Reichlin, and Small (2005) and Hansson, Jansson, & Löf (2005). The former uses a model-based uncertainty measure to assess the news content of data vintages that arrive within a given month. They find the largest declines in uncertainty after the releases of surveys and financial data. The latter reports that the inclusion of composite indexes of survey data into VAR models improves out-of-sample forecasts; note that this study uses a small data set of quarterly data.

activity. Further, soft data are published with very short publications lags, i.e. much sooner than the main macroeconomic aggregates. Lastly, survey data are subject to only very minor corrections. We provide three estimates of the current German GDP growth which are obtained 10, 6 and 2 weeks before the official release.

The remainder of the paper is organized as follows. Section 2 briefly describes the factors models. Section 3 outlines the automatic selection procedure for the variables of interest as well as the bridge models. The forecasting results are presented in Section 4. Section 5 discusses potential policy implications of the empirical results. Section 6 concludes.

2. Factor models

In the factor model framework, variables X_t, are represented as the sum of two mutually orthogonal unobservable components: the common component χ_t and the idiosyncratic component ξ_t. For a given t, $t = 1, \ldots, T$, the static factor model is defined by:

$$X_t = \Lambda F_t + \xi_t, \tag{1}$$

where $X_t = [x_{1t}, \ldots, z_{nt}]'$ is a vector of n stationary time series and it is assumed that the series have zero mean and covariance matrix $\Gamma(0)$, Λ is the loading matrix such that $\Lambda = [\lambda_1, ..., \lambda_n]'$, the common components $\chi_t = \Lambda F_t$ are driven by a small number r of factors F_t common to all the variables in the model such that $F_t = [F_{1t}, ...F_{rt}]'$, and $\xi_t = [\xi_{1t}, ..., \xi_{nt}]'$ is a vector of n idiosyncratic mutually uncorrelated components, driven by variable-specific shocks.

2.1. *Stock and Watson (2002a, 2002b)*

Stock and Watson (2002a, 2002b) (SW) use static principal component analysis (PCA) to estimate the factors F_t. An eigenvalue decomposition of the estimated covariance matrix $\hat{\Gamma}_0 = T^{-1}\sum_{t=1}^{T} X_t X_t'$ provides the $(n \times r)$ eigenvector matrix $\hat{S} = (\hat{S}_1, \ldots, \hat{S}_r)$ containing the eigenvectors $\hat{S}_j$ corresponding to the r largest eigenvalues for $j = 1, \ldots, r$. The factor estimates are the first r principal components of X_t defined as $F_t^{SW} = \hat{S}' X_t$. To integrate dynamics in forecasting, SW propose an autoregressive model for the factors.

To take dynamics into account in modeling, another way to proceed is to model explicitly the dynamics of the factors F_t. More precisely, we assume that the dynamic factor model [DFM] representation is given by the following equation:

$$X_t = A(L) F_t + \xi_t, \tag{2}$$

where the common components $\chi_t = A(L) F_t$ integrate a linear dynamics where $A(L)$ is a $(n \times r)$ matrix describing the autoregressive form of the r factors. If we assume that there exists a $(n \times q)$ matrix $B(L)$ such that $B(L) = A(L)N(L)$ with $N(L)$ of dimension$(r \times q)$, then the dynamic factor is such that $F_t = N(L)U_t$ where U_t is a $(q \times 1)$ independent vector containing the dynamic shocks. It follows that the factor dynamics are described by:

$$A(L) F_t = B(L) U_t \tag{3}$$

This equation specifies a VAR(p) model for the factor F_t with lag polynomial $A(L) = \sum_{i=1}^{p} A_i L^i$. F_t is thus the $(r \times 1)$ vector of the stacked factors with $r = q(p + 1)$.

2.2. Doz, Giannone and Reichlin (2011)

Doz et al. (2011) (DGR) proposed a DFM for a large set of data based on a state-space representation. They introduce a parametric time domain two-step estimator involving PCA and Kalman filter to exploit both factor dynamics and idiosyncratic heteroscedacticity. The two-steps (2S) approach consists in first estimating the parameters by PCA. Then, in the second step, the factors are estimated via Kalman smoothing. DGR (2011) cast the model into a state-space form with Eq. (2) referring to the state equation and Eq. (3) referring to the space equation. The estimated factors are noted F_t^{2S}.

2.3. Forni, Hallin, Lippi and Reichlin (2004, 2005)

To estimate the dynamic factors and their covariance, Forni et al. HLR (2004, 2005) (FHLR) propose dynamic PCA in the frequency domain, also called generalized dynamic factor model, where they estimate the common factors based on generalized principal components in which observations are weighted according to their signal-to-noise ratio. They proceed in two steps. First, the density spectral matrix of the common and idiosyncratic components $\hat{\Sigma}_\chi(\theta)$ and $\hat{\Sigma}_\xi(\theta)$ are estimated. Inverse Fourier transformation provides the time-domain autocovariances of the common and idiosyncratic components $\hat{\Gamma}_\chi(k)$ and $\hat{\Gamma}_\xi(k)$ for k lags. In a second step, they compute the r linear combinations of X_t that maximize the contemporaneous covariance explained by the common factors $\hat{Z}'_j\hat{\Gamma}_\chi(0)\hat{Z}_j$, with $j = 1, \ldots, r$. This optimization problem can be reformulated as the generalized eigenvalue problem $\hat{\Gamma}_\chi(0)\hat{Z}_j = \hat{\mu}_j\hat{\Gamma}_\xi(0)\hat{Z}_j$, where $\hat{\mu}_j$ denotes the jth generalized eigenvalue and $\hat{Z}_j$ its $(n \times 1)$ corresponding eigenvectors. The factor estimates are obtained as $F_t^{FHLR} = \hat{Z}'X_t$, where $\hat{Z} = (\hat{Z}_1, \ldots, \hat{Z}_r)$ is the $(n \times r)$ matrix of the eigenvectors.

As recently suggested by Watson (2003), Boivin and Ng (2006), Barhoumi et al. (2010) and Caggiano, Kapetanios, and Labhard (2011), it is not necessary to use large databases in DFMs. Already a reasonable cross-sectional size leads to similar results than the use of very large data sets. Therefore, the present forecasting exercise employs factors extracted from 24 time series, which represent the monthly signals that help us to monitor the short-term behavior of GDP growth. See Appendix A for a description of the dataset.

3. Automated model selection procedure and bridge models

3.1. Automatic selection procedure

The data selection method has been designed to be as robust as possible and easily replicable at the same time. Relevant series are selected with an automatic model selection procedure which yields parsimonious short-run dynamic adjustment equations.[7] This procedure is particularly relevant from a practical point of view: it offers the possibility to quickly re-estimate models when changes in the data[8] modify the structure of the models, while still allowing for an economic interpretation of the models. The automatic model selection procedure is based on a general-to-specific (Gets) modeling strategy, proposed by David Hendry and implemented in an automatic

[7] Golinelli and Parigi (2005), Banerjee et al. (2005), Banerjee and Marcellino (2006) and Barhoumi et al. (in press) also used an automatic model selection procedure to build their bridge models.

[8] Such changes can be due to data revisions, changes in computing seasonally adjusted data (methods or parameters), as well as structural changes in the collected soft data and explanatory variables.

way by Hoover and Perez (1999).[9] As shown by Perez-Amaral, Gallo, and White (2005) and Castle (2005), Gets strategy is appropriate when there is a desire to conform to economic interpretation. In this study, we use GROCER[10] (Dubois, 2003), a computer program which implements the Gets modeling.

The automatic model selection procedure encompasses four basic stages when selecting a parsimonious undominated representation of an overly general initial model. The latter is denoted the general unrestricted model (GUM) and contains all the variables likely (or specified) to be relevant, including the maximum lag length of the independent and dependent variables. The four stages of the procedure are:

- the estimation and testing of the GUM;
- a pre-search process aiming at removing insignificant variables from the GUM;
- a multipath search procedure checking the validity of each reduction until terminal selections using diagnosis are accomplished – these terminal models are tested against their union until a unique undominated congruent model is selected;
- a post-search evaluation to check the reliability of the selection using overlapping sub-samples (refer to Krolzig & Hendry (2001) for further details).

As suggested by Krolzig and Hendry (2001), the following statistical tests are then implemented in the automatic model selection procedure: (i) the Lagrange Multiplier test for serial correlation in the residuals up to 5 lags, (ii) normality tests, (iii) tests for quadratic heteroscedasticity between regressors, and (iv) Chow in-sample predictive failure test on 50% and 90% of the sample. A multicollinearity diagnostic is also displayed.

3.2. Bridge models

The bridge equation relates quarterly average of the monthly explanatory variables (X_t) to quarterly GDP growth (Y_t). The general specification of the autoregressive-distributed-lag (ARDL) bridge model for q explanatory variables is as follows:

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i Y_{t-i} + \sum_{j=1}^{q} \sum_{i=1}^{k} \delta_{j,i} X_{j,t-i} + \varepsilon_t \tag{4}$$

where m is the number of autoregressive parameters, q is the number of explanatory variables, and k is the number of lags for the explanatory variables. The explanatory variables and their lags as well as the autoregressive parameters have been chosen from the automatic selection procedure.[11] The description and the source of all variables are given in Appendix A.

These BMs are designed to be used on a monthly basis. The index of industrial production (IPI, henceforth) is probably the most important and widely analyzed high-frequency indicator,

[9] An overview of the literature, and the developments leading to Gets modeling in particular, is provided by Campos, Ericsson and Hendry (2004). See Valadkhani (2004) for a discussion on macroeconometric modeling.

[10] GROCER is an open source econometric toolbox for the software Scilab, developed by Dubois and Michaux. For more information, refer to http://dubois.ensae.net/grocer.html. Krolzig and Hendry (2001) implemented Gets modeling in the computer program PcGets.

[11] As pointed out by, e.g., Ciccone and Jarocinski (2010) the variables chosen by the automatic selection procedure could be very sensitive to the particular time span of the sample. We have verified the stability of variables in sub-samples.

given the relevance of the manufacturing activity as a driver of the whole business cycle. However, the IPI is published with a much longer delay than surveys (around 40 days after the end of the month),[12] thus, it is less useful for early forecasting exercises. In the following, we thus propose a series of bridge models that are solely based on soft data. BMs taking into account the IPI among other explanatory variables are also provided for.

The bridge models are estimated by ordinary least squares (OLS) over the period from 1993Q1 to 2007Q4. Various residual diagnostic tests reveal no discernible specification errors.[13]

3.2.1. Models with IPI

This first group of three models was estimated using the Industrial Production Index in manufacturing. Other included exogenous variables are a consumer sentiment indicator (GFK) and the European Commission's confidence indicator for retail trade (RTEC). All equations include a constant and the first lag of the endogenous variable GDPDE_{t-1}. The BMs are as follows:

IPIMAN1

$$GDPDE_t = \underset{(1.19)}{0.119} - \underset{(-1.72)}{0.210} GDPDE_{t-1} - \underset{(-1.38)}{0.161} GDPDE_{t-3} + \underset{(4.93)}{0.265} IPI_t + \underset{(2.82)}{0.026} GFK_t$$

IPIMAN2

$$GDPDE_t = \underset{(0.91)}{0.102} - \underset{(-1.80)}{0.222} GDPDE_{t-1} + \underset{(4.76)}{0.256} IPI_t + \underset{(2.53)}{0.022} GFK_t$$

IPIMAN3

$$GDPDE_t = \underset{(2.39)}{0.720} - \underset{(-2.20)}{0.267} GDPDE_{t-1} - \underset{(-1.90)}{0.222} GDPDE_{t-3} + \underset{(4.63)}{0.245} IPI_t + \underset{(1.68)}{0.017} GFK_t + \underset{(2.11)}{0.023} RTEC_t$$

Generally, coefficients bear the expected signs. This is especially the case for the first lag of GDP's growth rate that exhibits the expected mean reversion; this specificity can be problematic for forecasting during monotonous and strong expansions or contractions of activity.

The coefficient of the IPI_t is highly significant in all three equations and important in size. This is symptomatic of the German economy, in which the industrial sector accounts for about 28% of the market economy's value added (against 17% for France and 24% for the euro area including Germany). The industrial sector's importance explains also the difficulties in forecasting German GDP. While value added (VA) in market services exhibits a standard deviation of 1.4 (for an average yearly growth rate of 2.6%), it is of 3.4 for manufacturing industries (given an average yearly growth rate of 0.7%).[14] Compared to services, higher volatility in industrial sectors is often induced by marked inventory cycles and investment strategies (see Imbs, 2006). The effects of 'big orders' i.e. the deliveries of airplanes, trains and the like are another particularity producing volatility in the industrial sector's production.

[12] Following the legislation introduced in 1998, the countries in the euro area are required to deliver IPI data with a delay of no longer than 45 days, necessary to collect information from a large number of production plants (see Ladiray and O'Brien, 2003).

[13] For some models the Newey-West HAC estimator was applied to correct heteroskedasticity.

[14] These calculations rely on data up the end of 2007, in order to avoid the bias possibly brought about by the high volatility of the crisis years.

Moreover, compared to its most important trading partner (France), the German IPI is more volatile (standard deviations of 3.4 versus 2.3). As the ongoing turmoil has shown, this type of volatility might be induced by Germany's export orientation, rendering German GDP more sensitive to the international business cycle.

The aforementioned factors cause German GDP to be relatively volatile. Given Germany's weight, this volatility largely affects European growth aggregates in turn. Hence, reliable forecasts of German GDP are of importance for policy makers also at the European level. When it comes to monetary policy decisions this is even more so the case, as they only feed through the economy after a certain lag (6–8 quarters, see Angeloni, Kashyap, Mojon, & Terlizzese, 2002; Mojon & Peersman, 2001; van Els, Locarno, Morgan, & Villetelle, 2001).

The consumer sentiment indicator (GFK_t) is also significant in all three equations. This is somewhat surprising as the German economy is known to be dependent on exports as a growth driver. The contribution of private consumption has been timid in recent years[15], but household's private consumption expenditures still account for an important part of GDP (57%). Finally, the confidence indicator for retail trade (RTEC) is significant in the IPIMAN3 model, again suggesting the importance that private consumption has for the evolution of German GDP.

3.2.2. Models without IPI

A second group of three models is estimated without relying on the IPI in manufacturing. These BMs include the following survey data: the expectations component of the IFO index (IFOFOR), company's anticipations at the six month horizon; sectors covered are industry, construction, retail and wholesale trade. An economic sentiment indicator for financial markets at the six month horizon (ZEW). The European Commission's confidence indicators for retail trade (RTEC) and the construction sector (CONSEC). The GFK's consumer sentiment indicator (GFK). As for the models based on the IPI, all equations include a constant and the lagged endogenous GDPDE^{t-1}. The BMs without IPI are as follows:

IFOGFK

$$GDPDE_t = \underset{(3.55)}{0.432} - \underset{(-2.12)}{0.280} GDPDE_{t-1} + \underset{(4.49)}{0.039} IFOFOR_t + \underset{(2.24)}{0.021} GFK_t$$

IFOCE

$$GDPDE_t = \underset{(4.68)}{1.03} - \underset{(-2.04)}{0.267} GDPDE_{t-1} + \underset{(3.76)}{0.034} IFOFOR_t + \underset{(2.15)}{0.022} RTEC_t$$

ZEWCE

$$\begin{aligned} GDPDE_t = {} & \underset{(5.13)}{1.40} - \underset{(-2.15)}{0.271} GDPDE_{t-1} + \underset{(2.99)}{0.019} CONSCE_t \\ & + \underset{(3.90)}{0.008} ZEW_{t-1} + \underset{(2.44)}{0.025} RTEC_t \end{aligned}$$

The first two models are based on IFOFOR, underlining the relevance of economic expectations for projections of the GDP. The third model relies on the EC and ZEW indicators. This is in line with Abberger (2007) and Marnet (1996) that also found IFO and ZEW indicators relevant

[15] Rather restrictive wage developments have restored Germany's export competitiveness especially *vis-à-vis* its European partners. Since the year 2000, nominal compensation per employee has increased by a yearly average of 1.2% in Germany against 2.9% in France, albeit an equally subdued evolution of inflation in both countries. Subsequently, German unit labor costs augmented by a yearly average of 0.5% (versus 2.0% for France), boosting German exports.

for forecasts of German GDP. Note that the ZEW indicator is introduced with one lag, implying the leading behavior of this indicator for German GDP growth. Finally, the confidence indicators for retail trade (RTEC) and the construction sector (CONSCE) contribute to explain evolutions in GDP growth.

4. Forecasting results

Models have been constructed to estimate current German GDP growth figures, in anticipation of their official release. Pseudo out-of-sample rolling forecasts are carried out to determine the final equations. The rolling forecasts have been implemented over the period 2002Q1–2008Q4 for pseudo out-of-sample with three forecasts by quarter. Parameters are estimated at each step but the specification of the models is unchanged.[16] This exercise takes the availability of data into account, under the assumption that a forecasting exercise will be implemented at each end of month. Therefore, the forecasting performance of bridge and factor models is assessed in three situations that mimic actual forecasting activity: (1) indicators are only available for the first month; (2) for the first two months; and (3) for all the whole quarter. An exception is the variable IPI for which we have only one and two months in the cases (2) and (3). Hence, the three estimates of GDP growth are obtained 10, 6 and 2 weeks before the official release, respectively. When data are missing for the rolling forecast procedure, the missing values are extrapolated using univariate AR models.[17] The latter rely on monthly data and their lag length is determined from the Schwarz information criterion.

For each quarter t, we provide with three forecasts for the current quarter (or nowcasts), $\hat{Y}_t^i$, for $i = 1, 2, 3$, which are obtained from the BMs estimated by OLS and from the factors implemented into the following forecasting model:

$$\hat{Y}_t^i = \beta' F_t^i + \phi(L) Y_{t-1}, \tag{5}$$

where F_t^i is the r-vector of estimated factors obtained by using one of the three methods (F_t^{SW}, F_t^{2S}, F_t^{FHLR}), $\beta = (\beta_1, \ldots, \beta_r)'$ is a coefficient vector of length r and $\phi(.)$ is a polynomial of order p. The $r + p + 1$ parameters of the model, namely $(\beta_1, \ldots, \beta_r, \phi_0, \phi_1, \ldots, \phi_p)$, are estimated by OLS. We do not use information criteria such as proposed by Bai and Ng (2002, 2007) for the number of static and dynamic factors, respectively, because these tests have been developed assuming that n and T tend towards infinity, an assumption not satisfied given the small size of our dataset. We rather apply the automatic model selection procedure to select the number of factors for the three methods r as well as lags for the autoregressive parameters p, by setting a maximum number for each specification: $r = 5$ and $p = 4$. Moreover, as the explained variable, GDP growth rate, is quarterly, we average the monthly estimated factors into quarterly factors in order to estimate the predicted value through equation (factors).

The root mean-squared error (RMSE) for the ith forecast is defined as:

$$RMSE(i) = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t^i)^2}, \tag{6}$$

[16] We perform pseudo out-of-sample forecasting because we do not have enough data for statistically evaluating out-of-sample forecasting.

[17] For the variable IPI we compare the extrapolation of the missing value from (i) an univariate AR model, and (ii) a model based on the European Commission's confidence indicator for German industry, available 40 days before the publication of the IPI.

where n is the number of quarters considered in the rolling forecast exercise, and Y_t is the flash estimate of the GDP growth.[18] We thus employed a vintage dataset of German GDP growth which covers the 2002Q1–2008Q1 period.[19] Benchmark results correspond to AR models and to naive projections.[20] Forecasts with the AR models present the following form, for all t:

$$\hat{Y}_t = \hat{\phi}_0 + \hat{\phi}_1 Y_{t-1} + \hat{\phi}_2 Y_{t-2} + \hat{\phi}_3 Y_{t-3} + \hat{\phi}_4 Y_{t-4} \tag{7}$$

where $\hat{\phi}_i$ are the estimated parameters. The naive projections are estimated by taking the last observation as the forecast, which is for all t:

$$\hat{Y}_t = Y_{t-1}. \tag{8}$$

For the two benchmark approaches, there is a single forecast by quarter as we do not include any monthly information. Results in terms of RMSE are presented in Table 1 as well as the ratio between each RMSE with that obtained from AR benchmark. Obviously, simply comparing RMSE-values does not take into account the sample uncertainty underlying observed forecast differences. This is why we additionally applied the test of equality of forecast performance proposed by Diebold and Mariano (1995).[21]

For the forecasts over the period 2002Q1–2008Q4 (Table 1), the RMSEs for the BMs and DFMs are generally lower than those of the naive and AR predictors. This result is generally confirmed when using the Diebold–Mariano tests. This finding confirms those obtained by Schumacher (2007) and Rünstler et al. (2009) when comparing DFMs and AR predictors.

As expected, the BMs excluding the IPI obtain better RMSEs than the BMs with IPI for the first forecast exercise, especially the CEZEW and IFOGFK models (with 0.35 and 0.36, respectively). The BMs including the IPI display a lower RMSEs for the second and third forecasts, especially the IPIMAN2 model (with 0.33 and 0.25, respectively), underlining the importance of the IPI for forecast accuracy. The RMSEs of the BMs with IPI generally decline over the three forecasts when information on the IPI becomes available. Overall, this shows that in fact changing the equations over the three forecasts appears to provide generally more precise forecasts and seems to be superior to keeping the same equation over time.

Out of the three DFMs, the best RMSEs are given by the FHLR approach whatever the forecasts, as found by Schumacher (2007). They are slightly larger than those of the BMs, except for the third forecasts.

5. Policy implications

In view of our empirical results some implications for policymakers and modelers may be derived. Overall, comparisons of different forecasting methods lead to a better understanding of the alternative approaches used and allow exploiting their complementarities.

[18] A flash estimate is defined as the earliest picture of the economy according to national accounts concepts, which is produced and published as soon as possible after the end of the quarter, using a more incomplete set of information than that used for traditional quarterly accounts.

[19] Schumacher and Breitung (2008) found that data revisions have no clear impact on the forecasting accuracy, as the use of final data leads to a performance similar to that with real time data.

[20] We do not use the models proposed by Baffigi et al. (2004) and Golinelli and Parigi (2007) for German GDP growth because some variables are not significant on our sample period.

[21] The modified Diebold–Mariano test of Harvey et al. (1997) has been implemented for our small number of out-of-sample forecasts.

Table 1
RMSEs for the first, second and third forecasts over the period 2002Q1–2008Q4.

Model	First	Second	Third	AR	Naive
CEZEW					
RMSE	**0.35**	0.35	0.35	0.41	0.47
Ratio	0.85*	0.85*	0.85**		
IFOCE					
RMSE	0.42	0.41	0.41		
Ratio	1.02	1.01	0.99		
IFOGFK					
RMSE	0.36	0.36	0.36		
Ratio	0.88*	0.88*	0.87*		
IPIMAN1					
RMSE	0.44	0.40	0.32		
Ratio	1.07*	0.98	0.78**		
IPIMAN2					
RMSE	0.40	**0.33**	**0.25**		
Ratio	0.98*	0.80*	0.61*		
IPIMAN3					
RMSE	0.41	0.37	0.31		
Ratio	0.99	0.90	0.76**		
SW					
RMSE	0.45	0.44	0.47		
Ratio	1.10**	1.07*	1.15*		
2S					
RMSE	0.44	0.44	0.46		
Ratio	1.07	1.07	1.12		
FHLR					
RMSE	0.36	0.34	0.37		
Ratio	0.88*	0.83*	0.90*		

Note: The best RMSEs are given in bold. Ratios of the RMSE with respect to AR model. *, ** and *** significant at the 10%, 5% and 1% level, respectively, for modified Diebold–Mariano tests (Harvey, Leybourne, & Newbold, 1997) against AR model.

The BMs generally provide very precise forecasts which are at the same time straightforward to interpret. Indicators that appear to be unrelated or only loosely linked to the target variable can be neglected. This has two advantages: (1) the BMs data sets are relatively small and, thus, not costly to update. (2) BMs predictions allow ‘telling the story’ of the forecast based on the explanatory indicators’ evolution. This is a very important feature in periods characterized by important and rapid changes, i.e. when it is necessary to quantify the relevance of specific events and to understand their origin at the same time.

DFMs, on the other hand, encompass all relevant information as no data are a priori discarded. This reduces the risk of omitting important predictors, and allows, hence, exploiting new information as soon as it becomes available. Related to that same reason, DFM-forecasting performance can, however, be slightly less efficient, as the ‘best’ indicators cannot be pre-selected from large data sets. Lastly, DFMs deliver forecasts that are less prone to regime-shift biases (Bulligan, Golinelli, & Parigi, 2010).

Therefore, the two approaches are fundamentally complementary, since the advantages of the one correspond to the limitations of the other. Thereby, the complementarily of the two approaches can contribute to enhance the precision of GDP forecasts during volatile periods as the ongoing one. And naturally the accuracy of forecasts can have important repercussions on the policy measures taken.

It is finally noteworthy that timely and accurate forecasts of German GDP growth rates are important for policy actions decided upon on a European level. Evolutions in Europe's biggest economy entail inevitable repercussions on economic data for the euro area, as Germany accounts for almost 30% of the area's aggregate output. Germany's economic importance for the euro area and the aforementioned high volatility in German growth rates further justify the implementation of the two complementary approaches. Thus, the present analysis closes a gap in the literature by proposing several, otherwise scarce forecasting models for German GDP growth rates.

6. Conclusion

In the present analysis, we compared bridge and dynamic factor models when it comes to nowcasting quarterly German GDP growth rate. This approach allows selecting explanatory variables among a large monthly data set including hard and soft data. We provided for three monthly forecasting exercises for a given quarter, including indicators of interest as soon as publication delays allowed for it. Furthermore, we carried out a rolling forecast exercise in order to assess the forecasting performance of the proposed models in pseudo out-of-sample forecasts. We found that it is possible to get reasonably good estimates of current quarterly GDP growth in anticipation of the official release. Our results showed that changing the BM's equations by including newly available monthly information provides generally more precise forecasts and is preferable to maintaining the same equation over the exercise's horizon. Finally, we found that forecast errors of the BMs are smaller than those of the DFMs.

Comparing the BMs and DFMs with the MIDAS approach that allows linking quarterly variables with monthly indicators is on our research agenda. It would also be interesting to use vintage data and to perform real out-of-sample forecasting.

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Appendix A. Appendix: Data

Table A1 .

Table A1
Information sources of the data.

Name	Source	Data type	Frequency	Publication lag
Quarterly National Accounts	Destatis	Hard	Quarterly	+45
Industrial Production Index	Destatis	Hard	Monthly	+40
Consumer sentiment indicator	GFK	Soft	Monthly	+0
Economic sentiment indicator (financial market)	ZEW	Soft	Monthly	+0

Table A1 (*Continued*)

Name	Source	Data type	Frequency	Publication lag
Economic sentiment indicator (industry, construction retail and wholesale trade)	IFO	Soft	Monthly	+0
Business surveys in retail trade	European Commission	Soft	Monthly	+0
Business surveys in construction	European Commission	Soft	Monthly	+0
Financial data	Datastream	Soft	Daily	+0

Note: publication lags correspond to the number of days after the end of the reference period.

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