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## RESEARCH ARTICLE

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# Forecasting Baden-Württemberg's GDP growth: MIDAS regressions versus dynamic mixed-frequency factor models

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## Abstract

Germany's economic composition is heterogenous across regions, which makes regional economic projections based on German gross domestic product (GDP) growth unreliable. In this paper, we develop forecasting models for Baden-Württemberg's economic growth, a regional economy that is dominated by small- and medium-sized enterprises with a strong focus on foreign trade. For this purpose, we evaluate the backcasting and nowcasting performance of mixed data sampling (MIDAS) regressions with forecast combinations against an approximate dynamic mixed-frequency factor model. Considering a wide range of regional, national, and global predictors, we find that our high-dimensional models outperform benchmark time series models. Surprisingly, we also find that combined forecasts based on simple single-predictor MIDAS regressions are able to outperform forecasts from more sophisticated dynamic factor models.

## KEYWORDS

backcasting, Germany, high dimensional, nowcasting, regional

## JEL CLASSIFICATION

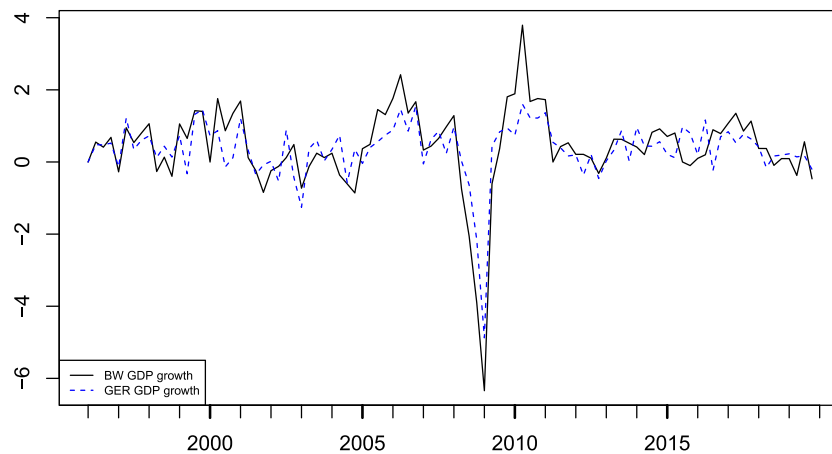
C32; C53; E37; R11

## 1 | INTRODUCTION

Projections of future economic development are important for policymakers and administrations with regard to public spending and tax revenue at both national and regional levels. This holds particularly true in federal states, like Germany, where the states have certain authorities and responsibilities like the police force, health services, education, job training, and culture. So far, the administration and policymakers in Baden-Württemberg (BW) do not use sophisticated econometric approaches to monitor economic developments. Therefore, the aim of this paper is to provide a multivariate forecasting model for the gross domestic product (GDP) growth of BW, an important industrial region of Germany, contributing about 15% to its GDP. As Germany is economically heterogenous across

regions, economic projections at the state level cannot be directly derived from the German national GDP. For the case of BW, the need for a specific model is also highlighted by Figure 1, which compares Germany's and BW's GDP growth and shows substantial differences in the trajectories despite both indicators apparently following the same business cycle. More precisely, the volatility of BW's GDP growth rate appears to be higher, which is also reflected by a stronger downturn in BW's GDP during the Global Financial Crisis but also by a more pronounced recovery thereafter.

Economically, BW is generally focused on the manufacturing sector, mainly composed of small- and medium-sized enterprises, and has a strong dependence on the automotive industry. Its economy hence is strongly export oriented, and therefore, the world economy and



**FIGURE 1** Baden-Württemberg (BW) versus Germany (GER) gross domestic product (GDP) growth. This figure plots GDP growth in % for BW (black solid line) and GDP growth % for Germany (blue dashed line) over the full sampling period spanning from 1996Q1 to 2019Q4 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

particularly the economic climate in its main trading partners seem to be of high relevance in the context of macroeconomic forecasting.

From an econometric perspective, we aim to exploit past and current information about a broad range of economic indicators to predict BW's GDP growth rate, which in a real-world setting involves two issues: First, GDP is observable quarterly, whereas many economic indicators are available at higher sampling frequencies. To avoid aggregation of higher frequency information and to exploit as much available information as possible, econometric approaches that allow for different sampling frequencies are necessary. Second, macroeconomic data are usually only available with substantial publication lags, that is, the distance between the release date and the reference period, which varies across indicators. Technically, this implies that the dataset used in forecasting will be unbalanced at the end of the observational period (so-called 'jagged' or 'ragged' edge data) because data will be not available for all time series at the model estimation and forecasting date(s). Particularly, BW's GDP growth—our target variable—has a minimum publication lag of 120 days with regard to the reference period. This implies that at the forecasting date, no observation for the previous quarter is available; and consequently, two step ahead forecasts are necessary with common time series model to obtain a prediction for the current period. According to Giannone et al. (2008) and Bańbura and Rünstler (2011), the corresponding one-step forecast actually is a *back-cast* of BW GDP growth (forecasting a value of a previous period), whereas the two-step-ahead forecast is called a *nowcast* (forecasting a value of the current period).

Specifically, we compare econometric approaches from two different classes: the approximate dynamic factor model (DFM) according to Mariano and Murasawa (2003) and Giannone et al. (2008) and mixed data sampling (MIDAS) regressions with forecast combinations according to Marcellino and Schumacher (2010) and Claudio

et al. (2020). Both frameworks are able to handle mixed-frequency variables and different publication lags caused by staggered and nonsynchronous data releases. The unbalanced nature of our data is accounted for either by estimating individual MIDAS regressions for each predictor or through aggregation weights in the DFM.

To obtain a realistic perspective on their performance, forecast models are evaluated using so-called 'vintages' of data, that is, datasets that include only information that is actually available to forecasters at a given point in time. More precisely, using the MIDAS and DFM models, we run three forecasting (nowcasting/backcasting) rounds within each quarter, always exploiting as much information as is available from the latest data releases. The accuracy of the predictions from our models is then primarily measured on the basis of the root mean square forecast error (RMSFE). An equal predictive ability across models is tested using the multivariate version of the Diebold–Mariano test (Mariano & Preve, 2012).

We find that single-predictor MIDAS regressions with forecast combinations perform well in regional economic forecasting exercises. Although both model frameworks appear to perform equally well for backcasts, our MIDAS-based forecast combinations outperform the DFM for nowcasts. The specification of the DFM seems to be an important issue for their relative forecasting performance. In particular, determining its parameters (number of factors, lags, and primitive shocks) on the basis of in-sample information criteria according to Bai and Ng (2002, 2007) yields overparameterized models that are themselves outperformed by smaller DFMs.

The remainder of this paper is structured as follows: Section 2 discusses the recent literature on macroeconomic forecasting with an emphasis on studies considering regional forecasting models for Germany. Section 3 contains an overview over available forecasting models and outlines the DFM approach and MIDAS regressions with forecast combinations. The

empirical results are presented in Section 4, which includes a detailed discussion of our predictors, model specification, and forecast evaluations. Finally, Section 5 summarizes the main findings and provides concluding remarks.

## 2 | RELATED LITERATURE

Forecasting macroeconomic variables with a large set of predictors has attracted a lot of attention in the literature. Whereas the majority of earlier studies focused on the United States (Bernanke & Boivin, 2003; Evans, 2005; Stock & Watson, 2002), partly attributed to the exceptional data availability, recent studies are more evenly distributed across industrialized countries and more frequently also consider regional forecasts.<sup>1</sup> Among those studies, Baffigi et al. (2004) forecasted euro area GDP using bridge equations. Bańbura and Rünstler (2011) also focused on the euro area but chose DFMs following Giannone et al. (2008). Angelini et al. (2011) explicitly contrasted the forecasting performance of bridge equations against DFM and found that the DFM outperforms bridge equations.

Germany, as the largest euro area economy, is often the subject of forecasting exercises. Schumacher (2007) compared the forecasting performance of different factor models on the basis of the example of German GDP. The author collected a dataset of 124 indicators that are all given at quarterly frequency so that mixed-frequency problems do not have to be considered. In contrast, Schumacher and Breitung (2008) forecasted German GDP growth using a DFM with 52 monthly and quarterly predictors. Recursive forecasts are evaluated over the period 1999Q2 to 2005Q1. Marcellino and Schumacher (2010) employed a so-called factor MIDAS approach, where estimated common factors act as regressors in the MIDAS regression framework. They applied factor MIDAS and DFM to forecast German GDP growth from 1992Q1 until 2006Q3. A two-step factor MIDAS performs similarly to large DFMs estimated with Kalman filtering. Further studies for Germany are Antipa et al. (2012) comparing the forecasting performance of bridge equations and factor models and Drechsel and Scheufele (2012) focusing on the effects of structural breaks induced by the global financial crisis. Heinisch and Scheufele (2018) proposed to forecast the individual components of German GDP from 2005Q1 to 2014Q4 using a DFM and MIDAS regressions with forecast combinations. However, their results only provide limited evidence that such a disaggregation results in a better predictive ability.

Another strand of literature attempts to forecast regional economic growth, which is often more difficult

owing to the unavailability of regional indicators or their availability with substantial publications lags, or (lower) sampling frequency Kholodilin et al. (2008) resorted to specifying a dynamic panel model with spatial effects to forecast GDP growth of the German states. As quarterly growth rates are not available for all 16 German states, the database comprises annual growth rates from 1991 to 2006. They concluded that pooling the data into a panel and modeling of spatial effects between regions help to improve the forecasting performance. Henzel et al. (2015) forecasted GDP growth for the Free State of Saxony and investigated the relative forecast contribution of hard and soft indicators. Lehmann and Wohlrabe (2015) forecasted GDP for two German states (Free State of Saxony and BW) and the region of Eastern Germany (comprising six states). They used data from 1996Q1 to 2010Q4 and entertained single-predictor autoregressive distributed lag (ADL) models with forecast combinations and the DFM following Giannone et al. (2008). They found that single-predictor models with forecast combination outperform large factor models. Finally, Claudio et al. (2020) forecasted East German GDP growth using MIDAS regressions with forecast combinations.

## 3 | METHODOLOGY

### 3.1 | Overview of forecasting approaches

As forecasting macroeconomic variables is important for policymakers, the theoretical literature on this topic is vast and has suggested a large number of different forecasting models. The most promising approaches incorporate not only the history of the target variable but also external information about other predictors. An important aspect of macroeconomic forecasting is to combine information available at different sampling frequencies.

One of the simpler forecasting models is based on so-called 'bridge equations' linking high-frequency variables to low-frequency ones within a linear regression model (Baffigi et al., 2004). A difficulty in the context of bridge equations is that only partial monthly information is available for the target quarter, so that the monthly variables have to be forecasted using auxiliary models. Another related approach is the MIDAS regression framework, which allows to estimate a model for the low-frequency target variable exploiting the high-frequency information by transforming the high-frequency variable into a low-frequency vector (Ghysels et al., 2004, 2016). Depending on the number of predictors (as well as the difference between low and high(er) sampling frequencies), dimensionality can become an important issue. Hence, Clements and Galvao (2009), Andreou et al. (2013),

<sup>1</sup> Bańbura et al. (2013) provided a review of the nowcasting literature and a list of references with applications to specific countries or regions.

Kuzin et al. (2013), and Claudio et al. (2020) suggested to employ single-predictor MIDAS models and to resort to forecast combinations to incorporate information from a large set of predictors in forecasting the target variable. Kuzin et al. (2011) compared the MIDAS approach against mixed-frequency vector autoregression (VAR) models, and Schumacher (2016) outlined the differences between bridge equations and MIDAS.

An alternative approach proposed in the literature is to summarize the information about economic predictors with a few common factors and to exploit their dynamic structure to obtain predictions. Dynamic mixed-frequency factor models can be understood as ‘large bridge equations’ combining monthly and quarterly frequencies (Giannone et al., 2008). Although the projection on all variables is infeasible, common factors provide a good approximation for the infeasible and overparametrized full model. This class of models is usually estimated within a state-space framework with Kalman filtering (Mariano & Murasawa, 2003) or within a Bayesian framework. Boivin and Ng (2006) provided guidelines on model specification and the selection of variables. Stock and Watson (2002), Angelini et al. (2006), and Schumacher and Breitung (2008) suggested to estimate DFMs with a maximum likelihood estimator (MLE) based on the expectation–maximization (EM) algorithm. Doz et al. (2011) provided consistency proofs for the two-step estimator proposed in Giannone et al. (2008), and Doz et al. (2012) showed that the EM-MLE is consistent. Besides these theoretical contributions, various authors applied DFMs in the context of nowcasting macroeconomic variables (see, for example, Bernanke and Boivin (2003), Marcellino et al. (2003), Evans (2005), Giannone et al. (2008), Bańbura and Rünstler (2011), and Andreini et al. (2020).

So far, it is still unclear which statistical model class is the most suitable for forecasting macroeconomic variables with many predictors. As most studies consider only one approach for their specific empirical application and focus on a single country or region, the literature so far neither provides guidance with regard to the choice of models in a specific forecasting exercise, nor whether a unanimously best choice even exists. However, some studies compare several alternative approaches. For example, Forni and Marcellino (2014) applied bridge equations, MIDAS regressions, and mixed-frequency VAR models. They found that factor-augmented MIDAS regressions seem to perform best in the context of nowcasting quarterly Euro area GDP components. Pirschel and Wolters (2018) considered three alternative forecasting approaches (factor models, Bayesian VAR, and model averaging techniques) using many predictors and found that Bayesian VAR and the Bayesian factor-augmented VAR

perform best in their forecasting exercise. In contrast, Carriero et al. (2019) compared four classes of multivariate forecasting models (dynamic stochastic general equilibrium [DSGE], factor-augmented distributed lag [FADL], MIDAS regressions, and Bayesian VARs) over four different subperiods of 5 years for seven countries. They found that factor-augmented models and equal-weighted combinations of single-predictor MIDAS regressions perform better than Bayesian VARs when dealing with large datasets. In light of these results and considering the available dataset, in our empirical application, we employ both a high-dimensional factor model and single-predictor MIDAS regressions from which we combine the individual forecasts.

### 3.2 | Dynamic factor models

Regression models like the VAR are designed for a small number of variables and are therefore typically affected by the curse of dimensionality in high-dimensional settings. In contrast, factor models allow to summarize information on many variables with a few common factors (Giannone et al., 2008). Mixed-frequency DFMs in the context of macroeconomic nowcasting combine data sampled at monthly and quarterly frequencies. We denote our monthly and quarterly data with  $y_t^M = (y_{1,t}^M, y_{2,t}^M, \dots, y_{N_M,t}^M)'$  and  $y_t^Q = (y_{1,t}^Q, y_{2,t}^Q, \dots, y_{N_Q,t}^Q)'$ , respectively. The frequency-specific vectors are combined to form the data vector  $y_t = (y_t^M, y_t^Q)'$ . The time index  $t$  denotes a calendar month; that is, our quarterly forecasts are computed for  $t = T + 3, T + 6, \dots$ , where  $T$  denotes the last observation of the sample. Note that we also aim to provide monthly forecasting rounds by using the information available from economic indicators until this point in time.

Our forecasts for period  $t$  are of the form  $\hat{y}_t^Q | \Omega_t^{N_M}, \Omega_{t-3}^{N_Q}$ , where  $\Omega_t^{N_M}$  is the information set containing  $N_M$  monthly variables at time  $t$  (during the ‘current’ quarter) and  $\Omega_{t-3}^{N_Q}$  is the information set containing  $N_Q$  quarterly variables at time  $t - 3$  (the previous quarter). Depending on the publication lag for the target variable, which is part of  $y_t^Q$ , the ‘current’ quarter might not coincide with the date of the chosen data vintage. Instead, it denotes the first month in which no observation for the quarterly target variable is available and, as in our case, constitutes a backcast of BW GDP growth. Usually, the accuracy of forecasts is observed to increase monotonically with each data release as more information about economic indicators becomes available (see, e.g., Bańbura & Rünstler, 2011).

Specifically, we estimate the approximate DFM for mixed-frequency data according to Forni and Reichlin (1996), Forni et al. (2000), Stock and Watson (2002), and



Mariano and Murasawa (2003):

$$y_t = \mu + \Lambda F_t + e_t, \quad e_{i,t} = \sum_{j=1}^K \rho_{i,j} e_{i,t-j} + \epsilon_{i,t}, \quad (1)$$

$$F_t = \Phi_1 F_{t-1} + \dots + \Phi_p F_{t-p} + B\eta_t,$$

where  $e_t = (\epsilon_{1,t}, \dots, \epsilon_{n,t})$  is a Gaussian white noise process with a diagonal covariance matrix so that  $\epsilon_{i,t} \sim i.i.d.N(0, \sigma_i^2)$  with  $E(\epsilon_{i,t}\epsilon_{j,t}) = 0$  for  $i \neq j$ . Further,  $\eta_t \sim i.i.d.N(0, I_q)$ ,  $E(e_t, u_t) = 0$ , and  $F_t$  is the  $r \times 1$  vector of common factors. The stochastic process  $\{F_t\}_1^\infty$  is assumed to be stationary.  $\mu$  is the intercept, and  $\Lambda$  is a matrix containing the factor loadings. As the vector of idiosyncratic components  $e_t$  can be serially correlated, the model is called an *approximate* DFM. Moreover,  $B$  is a  $r \times q$  matrix, where  $q \leq r$  and  $q$  denotes the number of dynamic factors (Stock & Watson, 2016) or primitive shocks (Bai & Ng, 2007). Imposing the normality assumption on  $\epsilon$  and  $\eta$  allows us to re-estimate the factors using the Kalman filter.

The mixed-frequency structure of the DFM follows the work of Mariano and Murasawa (2003). We assume that log GDP is integrated of order 1. Further, we assume that quarterly observations are available in the last month of the quarter. As log GDP is a flow variable, quarterly  $\ln gdp_t^Q$  is related to unobserved monthly  $\ln gdp_t^M$  via

$$\ln gdp_t^Q = \frac{1}{3} (\ln gdp_t^M + \ln gdp_{t-1}^M + \ln gdp_{t-2}^M), \quad (2)$$

and it holds for the quarterly growth rates,  $\Delta_3 \ln gdp_t^Q = \ln gdp_t^Q - \ln gdp_{t-3}^Q$ , that

$$\Delta_3 \ln gdp_t^Q = \frac{1}{3} (\Delta \ln gdp_t^M + 2\Delta \ln gdp_{t-1}^M + 3\Delta \ln gdp_{t-2}^M + 2\Delta \ln gdp_{t-3}^M + \Delta \ln gdp_{t-4}^M), \quad t = 3, 6, 9, \dots, T. \quad (3)$$

Equation (3) expresses the quarterly growth rates as a function of the monthly growth rates and thereby provides us with the aggregation weights for our DFM.<sup>2</sup> It has to be noted at this point that quarterly GDP is usually defined as the arithmetic mean of the (unobserved) monthly levels. However, the chosen representation as a geometric mean allows us to work with a linear state-space model, whereas the usual link over the arithmetic mean requires a nonlinear state-space model (Proietti & Moauro, 2006). We follow the recent literature (see, e.g., Andreini et al., 2020; Bańbura & Rünstler, 2011; Giannone et al., 2008) and use the outlined approach for a linear state-space model in this paper.

Further, making the contribution of quarterly and monthly frequencies explicit, a one-factor specification of

the DFM in Equation (1) can be expressed as

$$\begin{pmatrix} y_t^M \\ y_t^Q \end{pmatrix} = \begin{pmatrix} \mu^M \\ \mu^Q \end{pmatrix} + \begin{pmatrix} \Lambda^M F_t \\ \Lambda^Q \left( \frac{1}{3} F_t + \frac{2}{3} F_{t-1} + F_{t-2} + \frac{2}{3} F_{t-3} + \frac{1}{3} F_{t-4} \right) \end{pmatrix} + \begin{pmatrix} e_t^M \\ \frac{1}{3} e_t^Q + \frac{2}{3} e_{t-1}^Q + e_{t-2}^Q + \frac{2}{3} e_{t-3}^Q + \frac{1}{3} e_{t-4}^Q \end{pmatrix}, \quad (4)$$

where  $\mu = (\mu^M, \mu^Q)'$ ,  $\Lambda = (\Lambda^M, \Lambda^Q)'$ , and  $e_t = (e_t^M, e_t^Q)'$ . Optimal choices of  $r$  and  $q$  are based on information criteria (Bai & Ng, 2002, 2007). As these criteria evaluate in-sample fit whereas we are more interested in out-of-sample performance of the models, we provide robustness checks using out-of-sample results. For this matter, we compute the RMSFE over the evaluation period for different choices of  $r$  and  $q$ .

The model in Equation (4) is estimated within a state-space framework with Kalman filtering using two-stage least squares according to Stock and Watson (2002). We present the details of the state-space representation, using a one-factor specification ( $r = 1$ ) and  $p, q \leq 4$ , in Appendix C1.

### 3.3 | Single-predictor MIDAS regressions

The MIDAS framework according to Kuzin et al. (2011), Ghysels et al. (2016), and Claudio et al. (2020) is an alternative econometric approach to describe the variation of a target variable that is observed at some low frequency (e.g., quarterly) using predictors sampled at higher frequency (e.g., monthly). The basic idea of the MIDAS framework is to construct individual regressors from each high-frequency observation (of the high-frequency variable) within the low-frequency period and use them for estimation and prediction.

Formally, suppose  $\{Y_\tau, \tau \in \mathbb{Z}\}$  is a univariate process sampled at low frequency with low-frequency time index  $\tau$ , whereas  $\{X_t, t \in \mathbb{Z}\}$  is observed at high frequency, with high-frequency time index  $t$ . That is, within each low-frequency period  $t$ , the process  $x_t$  is observed  $m \in \mathbb{N}$  times. To *align* the different frequencies, the high-frequency variable  $x_t$  is stored in a so-called low-frequency vector  $(x_{m\tau}, x_{m\tau-1}, \dots, x_{m\tau-l})$ , which then is used for estimation and prediction. Assume, for instance, that  $y_\tau$  is observed quarterly whereas  $x_t$  is observed monthly, and we aim to describe  $y_\tau$  by variation in  $x_t$  from the past and current quarters (i.e., using all monthly observations within the respective quarters). For each quarter  $T = 1, \dots, n$ ,  $y_\tau$  is hence described by a linear combination of the variables  $x_{3\tau}, x_{3\tau-1}, x_{3\tau-2}, \dots, x_{3\tau-5}$ . In matrix notation, the corresponding MIDAS model is given

<sup>2</sup>Instead, annual growth rates,  $\Delta_{12} \ln gdp_t^Q = \ln gdp_t^Q - \ln gdp_{t-12}^Q$ , can similarly be expressed as a function of monthly growth rates. However, the aggregation weights would be different.

by

$$\begin{bmatrix} y_2 \\ \vdots \\ y_n \end{bmatrix} = \alpha + \begin{bmatrix} x_6 & x_5 & x_4 & x_3 & x_2 & x_1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{3n} & x_{3n-1} & x_{3n-2} & x_{3n-3} & x_{3n-4} & x_{3n-5} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \end{bmatrix} + \begin{bmatrix} \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}, \quad (5)$$

where the  $\beta_j$ s are the slope coefficients for the high-frequency variable transformed to a low-frequency vector corresponding to their within low-frequency period observations, and  $\varepsilon_t$  is a zero-mean error term.<sup>3</sup> It should be noted that estimation requires the number of observations of  $x_t$  to equal  $3n$ . Specifically, the model presented in Equation (5) can be estimated by ordinary least squares (OLS) without further restrictions, which corresponds to the so-called unrestricted MIDAS (U-MIDAS) model.<sup>4</sup>

Naturally, the MIDAS regression framework is not confined to a single high-frequency regressor or one high frequency. However, owing to the frequency alignment, parameter proliferation can become a serious issue in MIDAS models with both the number of high-frequency regressors and the number of lags of the high-frequency variable(s). The literature on MIDAS regression discusses various approaches to circumvent this issue and to specify MIDAS models parsimoniously while still exploiting all relevant high-frequency information available. In essence, these approaches follow two different ideas: First, there are so-called *aggregates-based* MIDAS models where parsimony is reached by aggregating the  $m$  high-frequency data points of the high-frequency variable observed within a low-frequency period, such that the high-frequency information is condensed in only *one* regressor. This means that the number of parameters is reduced from  $m$  to a minimum of one parameter per low-frequency lag included. The second approach, by contrast, builds on the idea of ‘genuine’ parsimony and involves estimating individual MIDAS models for each economic indicator and using

forecast combinations to incorporate information from every indicator.

There are various ways to aggregate the within low-frequency period high-frequency observations, the simple arithmetic mean being the most simple one. Ghysels et al. (2004) instead proposed to formulate the higher frequency part of MIDAS regressions in terms of aggregates given by  $\tilde{x}_\tau$ :

$$\beta(L)'x_{t,0} = \sum_{j=0}^l \beta_j x_{\tau m-j} = \sum_{r=0}^q \lambda_r \tilde{x}_{\tau-r},$$

where  $l$  is the number of high-frequency lags whereas  $q$  denotes the low-frequency number of lags. The aggregates,  $\tilde{x}_{\tau-r} = \tilde{x}_{\tau-r}(\delta_r) = \sum_{s=1}^m w_r(\delta_r; s)$ , depend on a weighting function  $w_r(\delta_r; s)$ , which aggregates the high-frequency information within the low-frequency period and is governed by its parameter vector  $\delta_r$ . To ensure that the weights assigned to the high(er) frequency observations add to one, Ghysels et al. (2004) suggested the following form for the weighting function:

$$w_r(\delta_r; s) = \frac{\psi_r(\delta_{r;s})}{\sum_{j=1}^m \psi_r(\delta_{r;j})}, \quad s = 1, \dots, m,$$

where  $\psi_r(\cdot)$  denotes some underlying functional form. Although various different functional forms, for example, the beta function or the log-Cauchy can be considered, the exponential Almon lag polynomial is commonly used in the literature (Claudio et al., 2020). In contrast to simple time averaging, this approach enables to exploit the timing of information because different weights are assigned to more recent and more past observations by the functional form. However, more advanced estimation procedures than conventional least squares are necessary for aggregates-based MIDAS regressions based on functional constraints (restricted MIDAS models). Note that the parameters for the functional constraint and the MIDAS regression parameters are estimated simultaneously, which requires a more complex numerical optimization. Besides the need for more advanced estimation methods, another drawback of this approach is that the functional constraint could be invalid such that the weighting scheme is not appropriate (Feroni et al., 2015). Particularly, in a situation where the discrepancy in the sampling frequencies between the low and high(er) frequency variable(s) is small (e.g., from monthly to quarterly) and only few (low-frequency) lags of the high-frequency variable(s) are necessary, Feroni et al. (2015) proposed to consider U-MIDAS models instead of using a functional form for parameter estimation.<sup>5</sup>

<sup>3</sup>Specifically, in our illustration,  $\beta_0$  ( $\beta_1/\beta_2$ ) is the coefficient for the high-frequency information observed in the third (second/first) month of the contemporaneous quarter  $t$ . Likewise,  $\beta_3$  ( $\beta_4/\beta_5$ ) is the coefficient for the high-frequency information observed in the third (second/first) month of the previous quarter  $t-1$ .

<sup>4</sup>Note that employing OLS for MIDAS model estimation implies that the weight on each (lagged) intermediate sampling is unconstrained, which might be in contrast to economic reasoning and thus be seen as a disadvantage of this approach. Especially, it might be plausible to presume that more recent observations of a high-frequency variable are more important for the future variation of the outcome variable and thus should receive a higher weight.

<sup>5</sup>On the basis of Monte Carlo simulations, Feroni et al. (2015) demonstrated that under this condition, U-MIDAS models often outperform

Estimating single-predictor models (Clements & Galvao, 2009; Claudio et al., 2020) appears particularly useful in forecasting exercises involving a large set of high-frequency indicators because it not only limits the models' dimensionality but also mitigates issues associated with multicollinearity. In contrast to the above-described aggregates-based MIDAS models that employ functional constraints, these single-predictor MIDAS models, usually, can be estimated by least squares without any further restrictions, which may generally be an advantage when only a limited number of observations are available. Furthermore, estimating separate models for each (high-frequency) indicator is also useful in a setting where the number of observations available differs strongly across the (high-frequency) indicators considered (ragged-edge data structure), as is typical in the context of macroeconomic forecasting. Precisely, from the perspective of forecasting, estimating separate MIDAS models appears advantageous compared with one high-dimensional model because these models can exploit all information available for each indicator up to the forecasting date. In contrast, in a single high-dimensional model, the observational period for all indicators would be restricted to the predictor with the fewest observations.

### 3.4 | Forecast combinations

The single-predictor MIDAS regressions produce individual forecasts of GDP growth. It is well-known that combining individual forecasts can improve the forecast performance, when no single dominant forecast exists and the underlying forecasting models reflect some heterogeneity in information sets (Timmermann, 2006). In this paper, we try several weighting schemes to exploit the information contained in our single-predictor regressions. Specifically, we consider (i) the mean forecast combination so that each forecast receives the same weight, (ii) the trimmed mean where we exclude the highest 5% and lowest 5% of the forecast values (Stock & Watson, 2004), and (iii) a scheme for adaptive forecasting weights (Drechsel & Scheufele, 2012). Whereas the mean forecast weights are constant across forecasting periods, the weighting schemes (ii) and (iii) produce weights that are time-varying.

For the construction of the adaptive forecasting weights, we ignore correlations across forecasts, and we compute them as relative performance weights in the spirit of Stock and Watson (2001). Our goal is to construct weights for each forecasting period that minimize the mean square error (MSE) over all previous forecasting periods. In forecasting period  $T+h$ , we collect the

previous  $h-1$  observed values of  $y_t$  in the vector  $Y$  and the  $h-1$  forecasts obtained from  $K$  single-predictor models in the matrix  $X$ , so that

$$Y = \begin{pmatrix} y_{T+1} \\ \vdots \\ y_{T+h-1} \end{pmatrix}, X = \begin{pmatrix} \hat{y}_{T+1}^{(1)} & \hat{y}_{T+1}^{(2)} & \cdots & \hat{y}_{T+1}^{(K)} \\ \vdots & \vdots & & \vdots \\ \hat{y}_{T+h-1}^{(1)} & \hat{y}_{T+h-1}^{(2)} & \cdots & \hat{y}_{T+h-1}^{(K)} \end{pmatrix}. \quad (6)$$

To estimate the optimal forecast weights  $w = (w_1, \dots, w_K)'$  minimizing the MSE for the  $h-1$  previous periods, we solve the following optimization problem:

$$\min_{w \in \mathbb{R}^K} \|Y - Xw\|^2, \text{ subject to } \sum_j w_j = 1, 0 \leq w_j \leq 1 \quad \forall j, \quad (7)$$

which involves two constraints. First, we follow Granger and Ramanathan (1984) and Diebold (1988) and impose that the weights sum to 1. Thereby, we ensure that the forecast errors are serially uncorrelated. Additionally, we impose the convexity constraint, which prohibits that the combined forecast lies outside the range of the individual forecasts. The problem can easily be solved with constrained least squares after initializing the algorithm with equal weights for the first three forecast combinations. The adaptive forecasting weights are computed individually for one-step-ahead and two-step-ahead forecasts. Like in the case of the trimmed mean forecast, the weights are time-varying and allow us to visualize which variable moves in and out of the set of relevant predictors and when this happens. Specifically, we draw heatmaps for backcasts and nowcasts where higher forecasting weights are marked with darker red areas. Our adaptive forecasting weights are conceptually similar to the approach taken by Heinisch and Scheufele (2018), who used combination weights based on ranks computed from the models' past performance. We note that adaptive weights are persistent so that an exceptional (but random) performance of one predictor might lead to higher weights of this predictor in subsequent periods. In principle, this can lead to a worse forecasting performance compared with the (trimmed) mean forecast if the importance of each predictor changes substantially from period to period.

## 4 | FORECASTING BADEN-WÜRTTEMBERG'S GDP GROWTH

### 4.1 | Data

For forecasting BW's GDP growth, we rely on a large set of indicators, covering the period 1996M1 to 2019M12. An ideal dataset for regional economic forecasts consists of a mixture of timely and high-quality indicators. These indicators are usually available at higher frequency and with shorter publication lags than data on GDP and its components. We distinguish between 'hard' and 'soft'

restricted MIDAS models in the context of forecasting, even when the true data-generated process is a restricted MIDAS model.

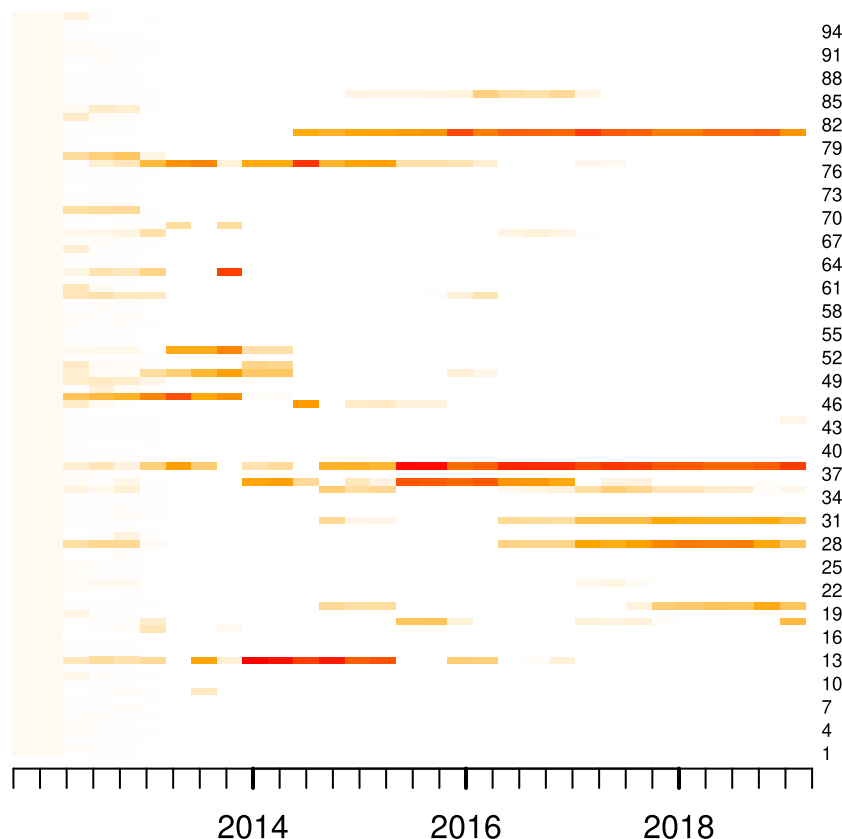


indicators. According to Bańbura and Rünstler (2011) and Bańbura et al. (2013), market expectations are labeled as ‘soft’ indicators, whereas indicators of real activity that measure certain components of the GDP are called ‘hard’ indicators. However, the variable selection is often limited by the availability of historical *regional* time series. In our case, we are restricted by the availability of regional ‘hard’ indicators, which are rarely available over the full sampling period. Hence, we extend the dataset to include national and global indicators to improve the forecasting performance of our high-dimensional forecasting models. Our aim is to obtain information about the intraquarter regional developments and about relevant national and international factors that potentially influence BW’s growth path. For example, we include the GDP growth of the top 5 trading partners of BW to model the global economic environment and to capture the economic growth of those trading partners (see also Kopoin et al., 2013, for the importance of international indicators). In contrast to Lehmann and Wohlrabe (2015), who had to rely on temporally disaggregated regional GDP data, we obtain seasonally adjusted quarterly growth rate data for BW from the Statistical Office of BW.

Specifically, our dataset includes real variables (e.g., new orders/turnover of selected industries like the manufacturing and construction industry, vacancies, and

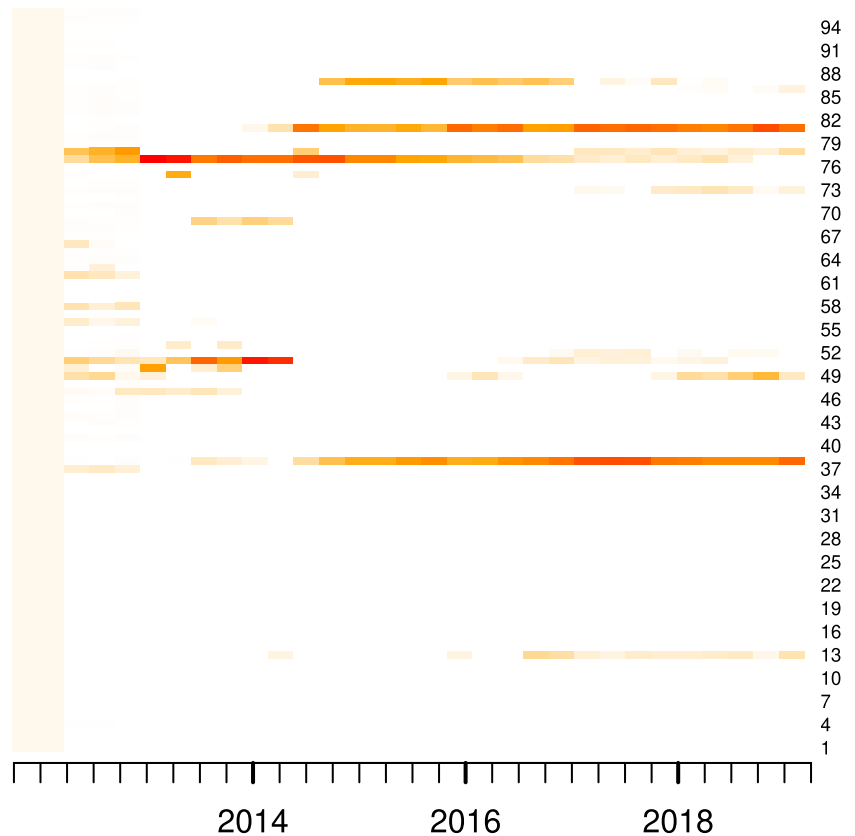
employment rates), prices, wages, money, and credit aggregates. Further, we include business surveys (ifo Institute or European Commission), expert surveys (ZEW—Leibniz Centre for European Economic Research), consumer climate surveys (Ifo Institute or GfK), and other available indicators of economic sentiment to obtain a timely measure of economic growth. Financial variables like the German DAX and the U.S. S&P 500 are also included (see Andreou et al., 2013, for a discussion of financial data in macroeconomic forecasting models). In total, we include 95 predictors (16 quarterly indicators and 79 monthly indicators). For a full list of predictors, see Table C2 in Appendix E1. Our dataset spans the period from 1996M1 to 2019M12. Most predictors are available over the full sampling period, and all variables are available after 2001M1.

Each indicator variable has its specific release date and corresponding publication lag. As the release dates can vary each month, we consider the average publication lag in days. We only consider vintages at the end of the month and, hence, do not explicitly model the intramonth flow of data. We define that quarterly observations are computed at the end of the month such that Q1 := March 31, Q2 := June 30, Q3 := September 30, and Q4 := December 31. Most time series are not available in a seasonally adjusted form, and we employ the X-13ARIMA-SEATS procedure



**FIGURE 2** Heatmap for adaptive one-step-ahead forecasting weights. This displays a heatmap for the adaptive forecasting weights over the evaluation period spanning from 2012Q1 to 2019Q3. Higher weights are indicated by darker red areas. Note that the algorithm must be initialized, which is accomplished by giving the predictors equal weights for the first three periods. The variable number on the right corresponds to the variable coding in Table C2 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

two-step-ahead forecasting weights. This displays a heatmap for the adaptive forecasting weights over the evaluation period spanning from 2012Q2 to 2019Q3. Higher weights are indicated by darker red areas. Note that the algorithm must be initialized, which is accomplished by giving the predictors equal weights for the first three periods. The variable number on the right corresponds to the variable coding in Table C2 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



for seasonal adjustment.<sup>6,7</sup> The choice of growth rates determines the importance of seasonal patterns on the time series' trajectory. We follow Mariano and Murasawa (2003) and compute month-on-month growth rates.<sup>8</sup> Alternatively, one could also consider annual growth rates, which would eliminate the seasonal pattern by construction. We entertain both alternatives and use the latter one as a robustness check.

We substitute missing observations (not part of the jagged-edge) and outliers using the outlier correction methodology presented in Giannone et al. (2008). Here, observations lying more than 4 interquartile range (IQR) from the median are substituted by their median value. Stationarity transformations are used to construct a series of first differences or growth rates (monthly growth rates or quarterly growth rates) if necessary. We test all variables for a unit root to check whether the stationarity transformations resulted in a set of stationary time series. Finally, all variables are standardized (transformed to have a zero mean and unit variance) for use in DFMs to eliminate scale effects.

<sup>6</sup>We use the *seasonal* R package to extract the seasonally adjusted time series.

<sup>7</sup>If seasonally adjusted data are obtained, we have to account for this in the construction of our monthly vintages, where we not only add the most recent observation to our vintages but also revise the complete time series.

<sup>8</sup>Giannone et al. (2008) used 3-month growth rates, which result in a 'smoother' time series. This type of growth rates is often used if the noise component of monthly predictors is relatively large.

## 4.2 | Forecasts and forecast evaluation

We use an expanding window approach to evaluate our forecasting models. Taking into consideration that we need a sufficiently large number of observations to estimate the coefficients of our models and a sufficiently long forecast evaluation period to run equal accuracy tests, we choose the following division of our sampling period. The initial estimation period spans from 1996Q1 to 2011Q4 comprising 65 quarterly observations and 195 monthly observations. The forecast evaluation period from 2012Q1 to 2019Q3 provides us with 31 quarterly observations, which can be considered sufficiently long compared with, for example, Schumacher and Breitung (2008) evaluating 24 forecasts in their forecasting exercise. Four quarters of our evaluation period have negative or zero growth rates, whereas 27 quarters have positive growth rates.

We evaluate a sequence of forecasts for different monthly real-time vintages that correspond to the information available at this point in time. Specifically, we build three quarterly forecasts on the basis of the information available in Month 1 to 3 for each quarter. As the publication lag for BW GDP growth is 120 days, we evaluate the backcast (one-step-ahead forecast at the vintage) and nowcast (two-step-ahead forecast at the vintage) of the

TABLE 1 Backcasting BW GDP growth

Forecast	MFE	MAFE	RMSFE	MaxAFE	DM
DFM M1	-0.0992	0.2835	0.3445	0.7204	0.05243
DFM M2	-0.0879	0.2739	0.3326	0.7057	0.03343
DFM M3	-0.1017	0.2755	0.3385	0.7154	0.04364
MIDAS Mean M1	0.0913	0.2696	0.3422	0.7008	0.06304
MIDAS Mean M2	0.0892	0.2675	0.3407	0.7636	0.06847
MIDAS Mean M3	0.0887	0.2686	0.3409	0.7711	0.07714
MIDAS Trimmed M1	0.0842	0.2672	0.3396	0.7067	0.05453
MIDAS Trimmed M2	0.0848	0.2659	0.3392	0.7382	0.06134
MIDAS Trimmed M3	0.0823	0.2645	0.3377	0.7435	0.06641
MIDAS Adaptive M1	0.0373	0.2740	0.3307	0.6518	0.06604
MIDAS Adaptive M2	0.0322	0.2508	0.3141	0.6862	0.03268
MIDAS Adaptive M3	0.0496	0.2560	0.3197	0.6759	0.04530
AR1	-0.0134	0.3478	0.4233	0.7620	0.63910
ARMA	0.0141	0.3635	0.4206	0.7775	0.64900
Constant growth	0.0151	0.3696	0.4441	0.9863	-

Note: The forecast evaluation period spans from 2012Q1 to 2019Q3 (31 quarterly observations). DFM denotes the *approximate* dynamic mixed-frequency factor model for Month 1 (M1), Month 2 (M2), and Month 3 (M3) of a quarter. Results are based on a two-factor specification with  $p = 1$  and  $q = 1$ . MIDAS Mean denotes the equal weights combination of single-predictor MIDAS regressions, MIDAS Trimmed denotes the forecast combination with 5 % lateral trimming, and MIDAS Adaptive uses weights on the basis of the previous period's MSE optimization. The constant growth forecast takes the mean growth over the previous periods. AR1 denotes the autoregressive model with lag order 1, and the ARMA forecast has a lag order chosen to optimize the AIC. The minimum publication lag is assumed for quarterly data. The column marked by 'DM' reports  $p$  values for the Diebold–Mariano test with the constant growth model serving as the benchmark model. Abbreviations: AIC, Akaike information criterion; ARMA, autoregressive moving average; BW, Baden-Württemberg; GDP, gross domestic product; MAFE, mean absolute forecast error; MaxAFE, maximum absolute forecast error; MFE, mean forecast error; MSE, mean square error.

DFM and MIDAS model, respectively, against the forecasting performance of a recursively estimated constant growth model and autoregressive moving average (ARMA) models (Schumacher, 2007; Marcellino & Schumacher, 2010). More specifically, we compute the mean growth over the periods  $1, \dots, t-1$ , to provide a naive constant growth forecast for period  $t$ . Likewise, we recursively estimate ARMA models for periods  $1, \dots, t-1$ , and select the lag length on the basis of the Akaike information criterion (AIC). For the backcast and nowcast, we compute the one-step-ahead and two-step-ahead forecasts, respectively. We compute the RMSFE to evaluate the performance of high-dimensional forecasting models against our benchmark forecast models. Further, we report the mean forecast error (MFE), mean absolute forecast error (MAFE), and maximum absolute forecast error (MaxAFE) to gain additional insights into the forecast performance of each class of models.

The DFM is estimated within a state-space framework with Kalman filtering using two-stage least square according to Stock and Watson (2002).<sup>9</sup> According to

the in-sample information criteria proposed by Bai and Ng (2002, 2007), we arrive at the following optimal specification of parameters:  $r = 5$ ,  $q = 5$ , and  $p = 4$ . For comparison, we find in the literature that Bańbura and Rünstler (2011) chose  $r = 5$ ,  $q = 2$ , and  $p \in \{1, 2, 3\}$  to obtain their lowest RMSFE. In contrast, Marcellino and Schumacher (2010) chose a one-factor model for their DFM with  $p \in \{1, 2\}$ . It appears that we have obtained a rather large model specification and, hence, check for the robustness of our results across all possible combinations of parameters, which provide a smaller model specification. It turns out that the performance of the DFM has a high variability across different specifications. The optimal out-of-sample performance in terms of RMSFE is reached for a two-factor model with  $p = 1$  and  $q = 1$ . Both factors have significant coefficients, and the residual autocorrelation is not significant for this model specification. Consequently, we henceforth choose the smaller DFM. Figure B3 in Appendix D1 shows that the first factor has high positive contributions from survey-based variables (Nos. 62–96), whereas the second factor has mostly negative weights for this group.

<sup>9</sup>We also tried estimation via the EM algorithm, but this did not produce equally well-performing forecasts. Although the EM-MLE has the conceptual advantage to be able to model factors for specific groups of variables (in our case, global, national, regional, hard, soft, labor, and dif-

ferent combinations thereof), it seems that the EM-MLE is not as robust as the two-stage estimator.

Forecast	MFE	MAFE	RMSFE	MaxAFE	DM
DFM M1	−0.1407	0.3569	0.4261	0.8755	0.7456
DFM M2	−0.1673	0.3548	0.4085	0.7887	0.5515
DFM M3	−0.1593	0.3364	0.4070	1.0128	0.5776
MIDAS Mean M1	0.1435	0.3225	0.3825	0.7800	0.2328
MIDAS Mean M2	0.1444	0.3273	0.3882	0.8251	0.2564
MIDAS Mean M3	0.1462	0.3231	0.3860	0.8406	0.2733
MIDAS Trimmed M1	0.1274	0.3159	0.3712	0.7493	0.1808
MIDAS Trimmed M2	0.1302	0.3219	0.3781	0.7824	0.1968
MIDAS Trimmed M3	0.1323	0.3179	0.3757	0.7991	0.2101
MIDAS Adaptive M1	0.1213	0.2997	0.3735	0.8184	0.0470
MIDAS Adaptive M2	0.1055	0.2997	0.3527	0.6295	0.0811
MIDAS Adaptive M3	0.1182	0.3016	0.3518	0.7630	0.0982
AR1	0.0060	0.4195	0.4734	0.8201	0.5117
ARMA	0.0385	0.4326	0.5000	0.8069	0.3624
Constant growth	0.0222	0.3753	0.4499	0.9863	-

TABLE 2 Nowcasting BW GDP growth

Note: The forecast evaluation period spans from 2012Q2 to 2019Q3 (30 quarterly observations). DFM denotes the *approximate* dynamic mixed-frequency factor model for Month 1 (M1), Month 2 (M2), and Month 3 (M3) of a quarter. MIDAS Mean denotes the equal weights combination of single-predictor MIDAS regressions, MIDAS Trimmed denotes the forecast combination with 5 % lateral trimming, and MIDAS Adaptive uses weights on the basis of the previous period's MSE optimization. The constant growth forecast takes the mean growth over the previous periods. AR1 denotes the autoregressive model with lag order 1, and the ARMA forecast has a lag order chosen to optimize the AIC. The minimum publication lag is assumed for quarterly data. The column marked by 'DM' reports *p* values for the Diebold–Mariano test with the constant growth model serving as the benchmark model. Abbreviations: AIC, Akaike information criterion; ARMA, autoregressive moving average; BW, Baden-Württemberg; GDP, gross domestic product; MAFE, mean absolute forecast error; MaxAFE, maximum absolute forecast error; MFE, mean forecast error; MSE, mean square error.

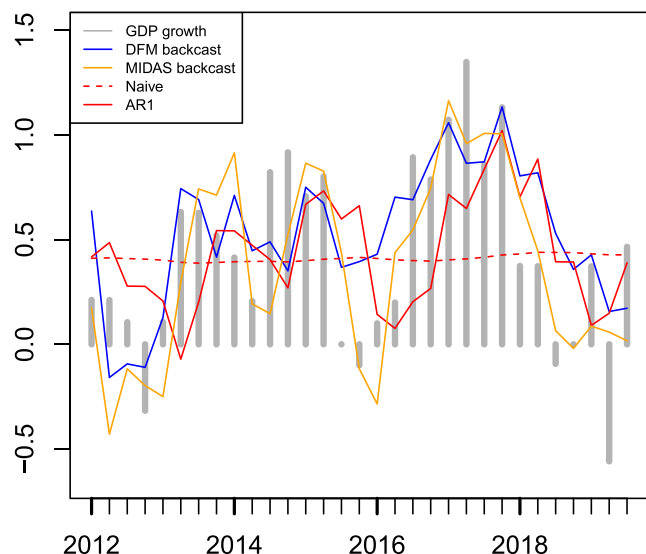
The MIDAS forecasts are based on single-predictor U-MIDAS models.<sup>10</sup> Imposing restrictions on the MIDAS regression, for example, using weights from the exponential Almon lag polynomial, did not improve the MIDAS forecasts. For each single-predictor model, we also include autoregressive lags of BW GDP growth to better capture the dynamic structure of the model. After the forecasts of the single-predictor models have been obtained, we use the forecast combinations as described in Section 3.4. We report three quarterly forecasts for each forecast combination scheme (mean, trimmed, and adaptive). Mean forecasting weights and trimmed mean forecasting weights are slightly outperformed by the adaptive weighting scheme. The adaptive forecasting weights for backcasts and nowcasts are depicted in heatmaps (see Figures 2 and 3), helping us to find out which variables are important for which period. We observe that many variables receive zero weights, which means that only a small subset of variables is needed at each given time to produce accurate forecasts. The highest weights for backcasts are chosen for the number of companies in the construction industry and the ifo

business climate index for the construction industry, both being regional indicators. Observing the developments in this industry seems to be a good early warning indicator for BW GDP growth. We do not see a clear pattern for variables that perform particularly well during crisis periods, although the harmonized Consumer Price Index (CPI) for the euro area briefly becomes important at the end of the European debt crisis. However, this can be attributed to the small number of quarters with negative growth rates during the evaluation period. The heatmap for nowcasts appears to be very similar to the one for backcasts except that more variables receive a zero weight. It features the same variables with high forecasting weights.

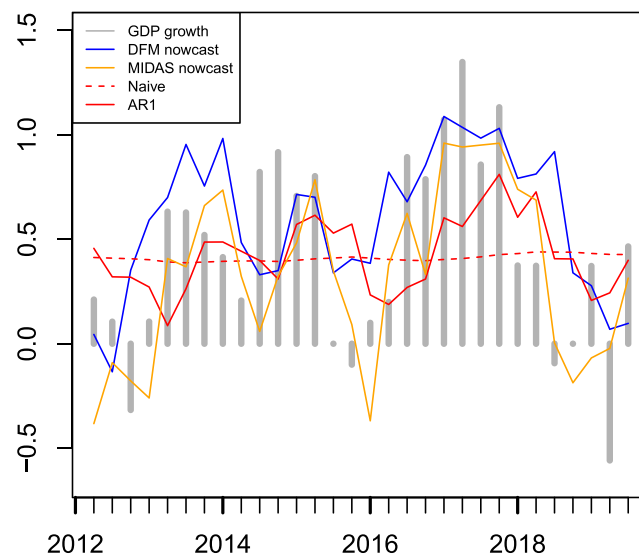
Tables 1 and 2 report the forecasting evaluation measures for the DFM and MIDAS regressions with forecast combinations. High-dimensional forecasting models seem to outperform classical time series models in both settings. However, the difference in RMSFE is greater for backcasts and much smaller for nowcasts. This emphasizes that high-dimensional forecasting models benefit from external information provided by the more timely predictors in our variable pool. If we try to forecast beyond the availability of additional predictor variables, these models tend to perform worse than less sophisticated benchmark models. Although the RMSFE of the DFM and MIDAS regressions

<sup>10</sup>Each model also includes lags of the target variable. The number of lags for the predictor and the target variable are selected by the AIC for each model individually.





**FIGURE 4** Forecast evaluation—backcast. This figure plots the observed gross domestic product (GDP) growth in % for Baden-Württemberg (BW) (bars), dynamic factor model (DFM) M3 backcast (blue line), mixed data sampling (MIDAS) Adaptive M3 backcast (orange line), the naive constant growth forecast (red dashed line), and the two-step-ahead AR(1) forecast (red line) over the evaluation period spanning from 2012Q1 to 2019Q3 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



**FIGURE 5** Forecast evaluation—nowcast. This figure plots the observed gross domestic product (GDP) growth in % for Baden-Württemberg (BW) (bars), dynamic factor model (DFM) M3 nowcast (blue line), mixed data sampling (MIDAS) Adaptive M3 nowcast (orange line), the naive constant growth forecast (red dashed line), and the two-step-ahead AR(1) forecast (red line) over the evaluation period spanning from 2012Q2 to 2019Q3 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

with forecast combinations is substantially smaller than the naive constant growth and AR benchmarks according to Tables 1 and 2, a more detailed analysis in Figures 4 and 5 reveals that these high-dimensional forecasting models do not insure against temporary relative forecast failure in some periods. For example, the DFM does not appropriately capture the slump in 2015, and the MIDAS forecasts only react with a one-quarter lag to growth rates turning from positive to negative. Comparing results with those reported in Lehmann and Wohlrabe (2015) is difficult because their evaluation period from 2003Q1 to 2010Q4 is completely embedded in our estimation period. Further, their GDP data are different with a much shorter publication lag (2 months instead of 4 months in our case).

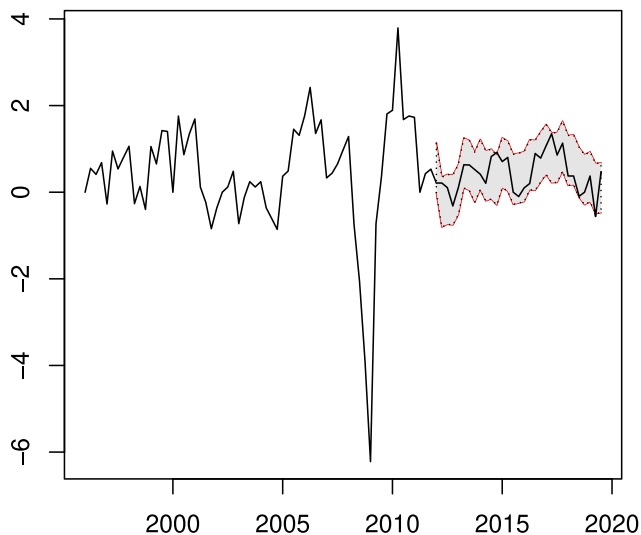
We conduct multivariate Diebold–Mariano tests (Mariano & Preve, 2012) for each forecasting round, testing the null hypothesis that DFM and the MIDAS models with mean, trimmed, and adaptive forecasting weights have an equal predictive ability. Although RMSFE are very similar across monthly vintages, equal predictive accuracy does not hold ( $p$  value: 0.007) for backcasts. However, equal predictive accuracy holds among DFM and MIDAS nowcasts for each monthly vintage. We also conduct pairwise Diebold–Mariano tests (Diebold & Mariano, 1995; Harvey et al., 1997) for which the constant growth model serves as the benchmark. The results are reported in the last column of Tables 1 and 2. Here, we find that the constant growth model is significantly outperformed

by most high-dimensional models when backcasting GDP growth. Surprisingly, we cannot reject the null hypothesis for any high-dimensional model (except for the MIDAS model with adaptive forecasting weights at the 10% level) applying the test to our nowcasts. This is indicative for the diminishing predictive power of forecasting models with many predictors if the forecasting horizon increases beyond the (very) short term.

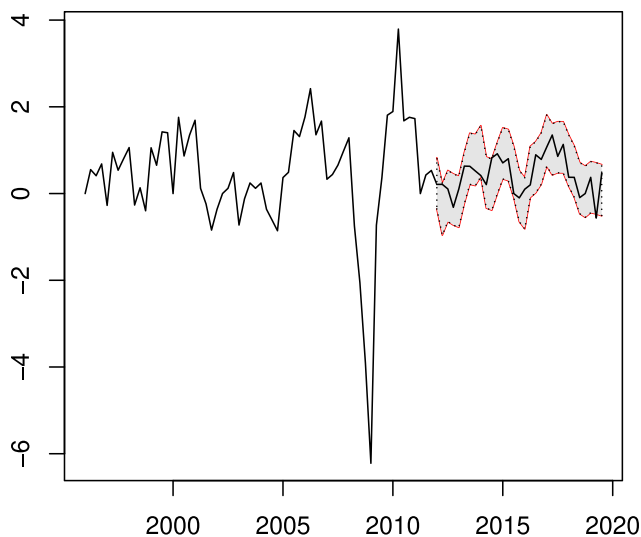
As policymakers are often interested in the confidence attached to the point estimates that are obtained from the DFM and the MIDAS regressions, we follow Bok et al. (2018) and construct probability intervals using the empirical distribution of the forecast errors. For this purpose, we first compute the forecast errors over the evaluation period and obtain the 2.5% and 97.5% quantiles of their empirical distribution. These values are added to the point forecasts to yield the prediction interval for each forecast. Figures 6 and 7 display the one-step-ahead (backcast) prediction intervals for the DFM and MIDAS, respectively. We observe that the MIDAS prediction intervals are slightly narrower.<sup>11</sup> However, both models seem to produce satisfactory results.

The publication lag depends on the timing of the vintage relative to the release date. For our main results,

<sup>11</sup> Similar plots for the two-step-ahead forecasts, as expected, display wider prediction intervals. The plots are not included to conserve space but can be obtained from the authors upon request.



**FIGURE 6** Prediction intervals (dynamic factor model [DFM] backcasts). This figure depicts Baden-Württemberg (BW) gross domestic product (GDP) growth trajectory (black) and prediction intervals at the 95% level (gray area bounded by dashed lines) for DFM M3 backcasts over the evaluation period spanning from 2012Q1 to 2019Q3 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



**FIGURE 7** Prediction intervals (mixed data sampling [MIDAS] backcasts). This figure depicts Baden-Württemberg (BW) gross domestic product (GDP) growth trajectory (black) and prediction intervals at the 95% level (gray area bounded by dashed lines) for MIDAS Adaptive M3 backcasts over the evaluation period spanning from 2012Q1 to 2019Q3 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

we assume the minimum publication lag, which is computed from the end of the quarter to the release date. For a monthly expanding estimation window, this does not reflect the true information set for all monthly forecasts. Hence, we also evaluate forecasts assuming the maxi-

**TABLE 3** Alternative specifications—backcasts

Forecast	MFE	MAFE	RMSFE	MaxAFE
<i>No publication lag</i>				
DFM M1	−0.1000	0.2721	0.3346	0.7160
DFM M2	−0.0967	0.2845	0.3435	0.7171
DFM M3	−0.0947	0.2728	0.3334	0.7042
<i>Maximum publication lag</i>				
DFM M1	−0.0589	0.2817	0.3442	0.7313
DFM M2	−0.1095	0.3015	0.3562	0.7192
DFM M3	−0.1271	0.2997	0.3552	0.6674
<i>No 'soft' indicators</i>				
DFM M1	0.0120	0.4059	0.5280	1.1441
DFM M2	0.0183	0.3359	0.4483	1.0433
DFM M3	0.0091	0.3270	0.4197	0.9795
<i>No 'regional' indicators</i>				
DFM M1	−0.0095	0.2446	0.3149	0.5920
DFM M2	−0.0020	0.2179	0.2870	0.6049
DFM M3	0.0176	0.2381	0.3036	0.6542
<i>No 'global' indicators</i>				
DFM M1	−0.2029	0.3448	0.4132	0.8388
DFM M2	−0.2199	0.3451	0.4193	0.8519
DFM M3	−0.2291	0.3453	0.4145	0.8565

*Note:* The publication lag depends on the timing of the vintage relative to the release date. Depending on the chosen vintage, the publication lag of quarterly indicators can vary. This table reports the forecast performance of the DFM for no publication lag (first panel) for all indicators, the maximum publication lag (second panel) assumed for quarterly indicators, exclusion of soft indicators (third panel), exclusion of regional indicators (fourth panel), and exclusion of global indicators (fifth panel). Abbreviations: DFM, dynamic factor model; MAFE, mean absolute forecast error; MaxAFE, maximum absolute forecast error; MFE, mean forecast error; RMSFE, root mean square forecast error.

imum publication lag as a robustness check. The forecast evaluation measures for the maximum publication lag are reported in the second panel of Tables 3 and 4 and help us to evaluate how important timely (quarterly) releases are. Note that we do not change the publication lag of BW GDP. If we did this, the quarterly variables would align again, and we would not be able to study the impact of more timely releases. The results for the specifications with minimum and maximum publication lag are very similar. Our results seem to be robust against a model for which the publication lags are adjusted each month.

To learn more about the contributions of certain groups of predictors to the forecasting performance, we exclude these groups from the DFM model and compare the RMSFE to our main results. For example, we exclude all regional indicators to assess the importance of monitoring regional economic developments. The results of several specifications of this kind are reported in panels 3–5 of Tables 3 and 4. We find that excluding 'soft' indicators have the strongest negative effect on the forecasting performance of the DFM. Excluding global indicators runs a close second. Surprisingly, the forecasting performance improves if we exclude our regional indicators. How-

**TABLE 4** Alternative specifications—nowcasts

Forecast	MFE	MAFE	RMSFE	MaxAFE
<i>No publication lag</i>				
DFM M1	−0.0829	0.3426	0.4162	1.0325
DFM M2	−0.1224	0.2886	0.3510	0.8757
DFM M3	−0.0962	0.2727	0.3376	0.7468
<i>Maximum publication lag</i>				
DFM M1	−0.0235	0.3314	0.3992	0.9659
DFM M2	−0.0569	0.3117	0.3596	0.7429
DFM M3	−0.0488	0.3251	0.3731	0.7330
<i>No 'soft' indicators</i>				
DFM M1	−0.0571	0.4091	0.5344	1.5849
DFM M2	−0.0776	0.4215	0.5198	1.1583
DFM M3	−0.0330	0.4173	0.5506	1.2157
<i>No 'regional' indicators</i>				
DFM M1	−0.0333	0.3292	0.4017	0.9083
DFM M2	−0.0442	0.3009	0.3503	0.7359
DFM M3	−0.0404	0.3037	0.3679	0.7254
<i>No 'global' indicators</i>				
DFM M1	−0.1835	0.3883	0.4677	0.9229
DFM M2	−0.2272	0.3817	0.4640	0.9944
DFM M3	−0.1922	0.3808	0.4569	0.9512

*Note:* The publication lag depends on the timing of the vintage relative to the release date. Depending on the chosen vintage, the publication lag of quarterly indicators can vary. This table reports the forecast performance of the DFM for no publication lag (first panel) for all indicators, the maximum publication lag (second panel) assumed for quarterly indicators, exclusion of soft indicators (third panel), exclusion of regional indicators (fourth panel), and exclusion of global indicators (fifth panel). Abbreviations: DFM, dynamic factor model; MAFE, mean absolute forecast error; MaxAFE, maximum absolute forecast error; MFE, mean forecast error; RMSFE, root mean square forecast error.

ever, the difference in the forecasting performance is not statistically significant, and the results for the DFM are in contrast to the results for MIDAS regressions where regional indicators receive high weights. Still, this tells us that the current selection of regional indicators can be improved to better capture regional economic developments.

Finally, we follow Bańbura and Rünstler (2011) and construct counterfactual datasets in which the publication lags are set to zero. Comparing these results to our main results shows the importance of incorporating the latest information available. 'Soft' indicators might perform better than 'hard' indicators if we take the latter's usually longer publication lags into account, but this feature is negated in this alternative specification. Although we do not see a large improvement for the backcasts, the improvement for nowcasting with zero publication lags is substantial compared with the main results (particularly at the third forecasting round in each quarter). The small difference for the backcasts can be explained by the fact that our target variable has an exceptionally long publication lag, which means that most indicators are already available contemporaneously; that is, they have an effective

publication lag of zero. This might also explain why backcasts of Forecasting Rounds 2 and 3 do not improve dramatically over those for Forecasting Round 1. Apparently, no relevant new information is added to the DFM in those months.

## 5 | CONCLUSION

This paper employs two high-dimensional forecasting approaches for the GDP growth rate of BW, involving a broad set of regional as well as national and global economic indicators. Although both model frameworks, the DFM and single-predictor MIDAS regressions with forecast combinations, seem to perform well during our evaluation period, we find the MIDAS-based predictions to be more robust and to slightly outperform the more sophisticated DFM. On the basis of our findings, we propose the use of single-predictor MIDAS models and forecast combinations derived from adaptive forecasting weights for similar regional forecasting exercises.

A general issue in our context, however, appears to be the availability of data. Put differently, because the forecasting performance of both models largely depends on the availability of timely high-quality economic indicators, we see potential for further improvements. Particularly, the lack of 'hard' indicators for regional economic developments seems to be a limiting factor. If it was possible to extend the dataset by more high-quality regional indicators, the forecast performance of both classes of models would certainly improve.

Furthermore, our setting is unusual in the sense that quarterly BW GDP, our target variable, has a publication lag of 120 days so that most predictors are available contemporaneously. Although the timely availability of indicators benefits forecasting models, which make use of many predictors in terms of short-run forecasting performance, the publication lag in our target variable requires us to attempt multiple-step-ahead forecasts to capture future economic developments. This, however, results in large forecast errors, which increase with the forecasting horizon. Therefore, more timely release dates (at least for preliminary releases of BW GDP components) should be sought by statistical offices and policymakers to obtain more accurate regional economic forecasts and to enable earlier evaluations of regional economic policies.

Finally, it should be noted that our evaluation period is not well-suited for testing forecasting model performance during economic downturns or crisis periods (e.g., the coronavirus disease 2019 [COVID-19] crisis) because the data contain only a small number of quarters with negative growth rates. Hence, our forecast combinations do not tell us much about the performance of our models in

future crisis periods. Additional research could focus on finding (high-dimensional) forecasting models or specific economic indicators that are robust during crisis periods.

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## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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## APPENDIX A: STATE-SPACE REPRESENTATION

Measurement equation ( $r = 1, p, q \leq 4$ ):

$$y_t = \mu + Hs_t \quad (\text{A1})$$

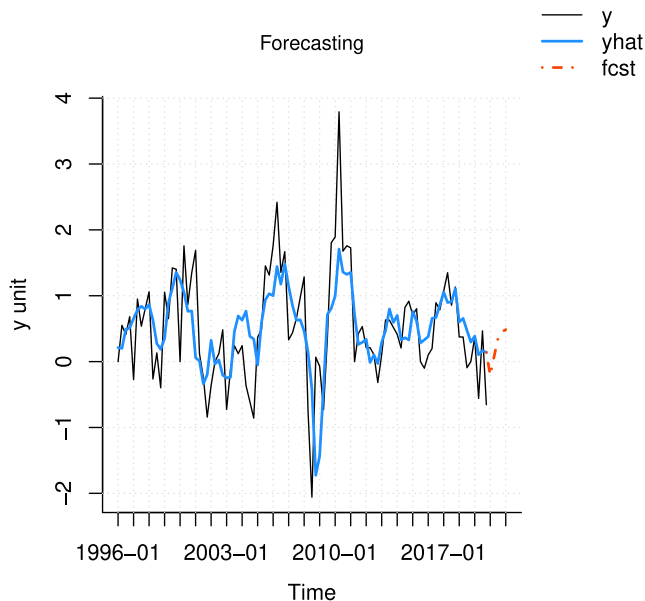
$$\begin{pmatrix} y_t^M \\ y_t^Q \\ y_t^Q \end{pmatrix} = \begin{pmatrix} \mu^M \\ \mu^Q \end{pmatrix} + \begin{pmatrix} \Lambda^M & 0 & 0 & 0 & 0 & I_{N_M} & 0 & 0 & 0 & 0 & 0 \\ \Lambda^Q & 2\Lambda^Q & 3\Lambda^Q & 2\Lambda^Q & \Lambda^Q & 0 & I_{N_Q} & 2I_{N_Q} & 3I_{N_Q} & 2I_{N_Q} & I_{N_Q} \end{pmatrix} \begin{pmatrix} F_t \\ F_{t-1} \\ F_{t-2} \\ F_{t-3} \\ F_{t-4} \\ e_t^M \\ e_t^Q \\ e_{t-1}^Q \\ e_{t-2}^Q \\ e_{t-3}^Q \\ e_{t-4}^Q \end{pmatrix}.$$

Transition equation:

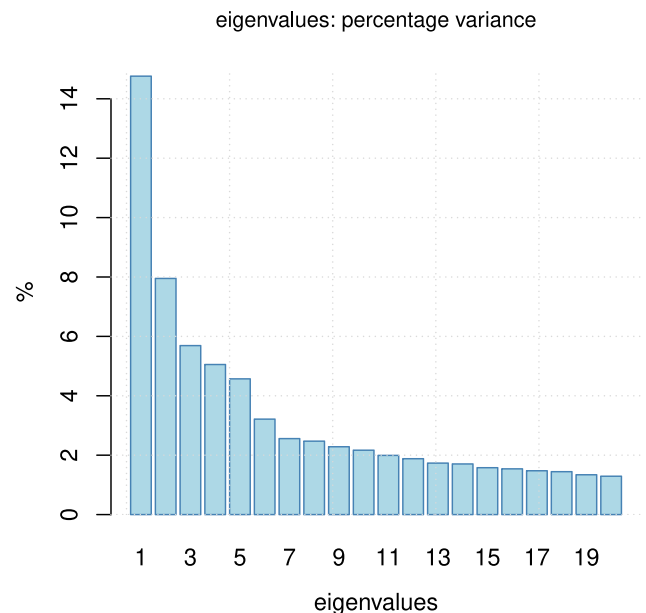
$$s_t = \Psi s_{t-1} + G v_t \quad (A2)$$

$$\begin{pmatrix} F_t \\ F_{t-1} \\ F_{t-2} \\ F_{t-3} \\ F_{t-4} \\ e_t^M \\ e_t^Q \\ e_{t-1}^Q \\ e_{t-2}^Q \\ e_{t-3}^Q \\ e_{t-4}^Q \end{pmatrix} = \begin{pmatrix} \Phi_1 & \Phi_2 & \Phi_3 & \Phi_4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \text{diag}(\rho_1, \dots, \rho_{N_M}) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \text{diag}(\rho_1, \dots, \rho_{N_Q}) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{N_Q} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{N_Q} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{N_Q} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & I_{N_Q} \end{pmatrix} \begin{pmatrix} F_{t-1} \\ F_{t-2} \\ F_{t-3} \\ F_{t-4} \\ F_{t-5} \\ e_{t-1}^M \\ e_{t-1}^Q \\ e_{t-2}^Q \\ e_{t-3}^Q \\ e_{t-4}^Q \\ e_{t-5}^Q \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ e_t^M \\ e_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}. \quad (A2)$$

## APPENDIX B: FIGURES

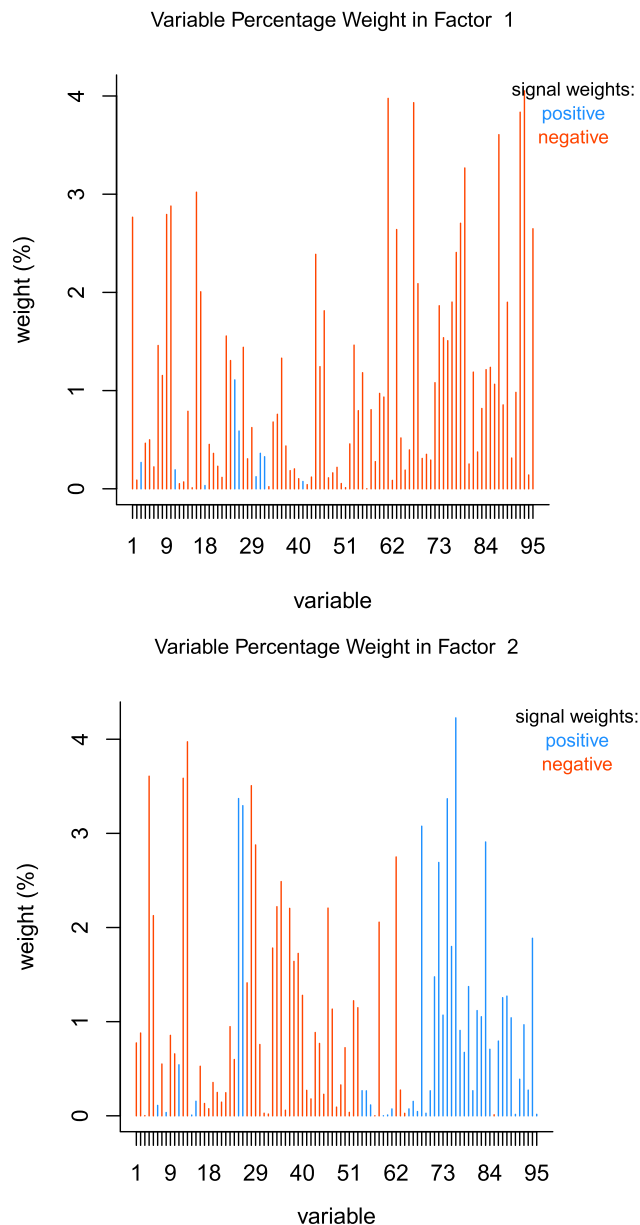


**FIGURE B1** Full-sample dynamic factor model (DFM). This figure depicts the in-sample fit (blue) of the DFM and forecasts (red) over the period spanning from 2020Q1 to 2021Q1. Note that the depicted Baden-Württemberg (BW) gross domestic product (GDP) growth trajectory (black) is cleaned from outliers (4 interquartile range [IQR] from the median) [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]



**FIGURE B2** Variability explained by each factor. This figure depicts how much of the variability in the set of predictors is explained by each factor [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

## APPENDIX C: TABLES



**FIGURE B3** Importance of each variable in both factor. This figure depicts the importance (in %) of each variable in both factors. The numbering of the variables corresponds to that in Table C2 [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

**TABLE C1** Variables

Variable	Description	Freq.	Min. lag	Source
<i>GDP</i>				
gdp.bw	GDP, Baden-Württemberg	Q	120	Statistical Office of Baden-Württemberg
gdp.ger	GDP, Germany	Q	45	Federal Statistical Office
gdp.private.cons.ger	GDP: private consumption, Germany	Q	55	Federal Statistical Office
gdp.gov.cons.ger	GDP: government consumption, Germany	Q	55	Federal Statistical Office
gdp.invest.equip.ger	GDP: investment: equipment, Germany	Q	55	Federal Statistical Office
gdp.invest.constr.ger	GDP: investment: construction, Germany	Q	55	Federal Statistical Office
gdp.gbr	GDP, Great Britain	Q	45	OECD
gdp.nld	GDP, Netherlands	Q	45	OECD
gdp.usa	GDP, USA	Q	45	OECD
gdp.che	GDP, Switzerland	Q	45	OECD
gdp.fra	GDP, France	Q	45	OECD
<i>Money &amp; Prices</i>				
M2.eu	Monetary aggregate M2, EU	M	30	European Central Bank
Harmon.cpi.eu	Harmonized CPI, EU	M	30	Eurostat
gdp.deflator.eu	GDP deflator, EU	Q	90	European Central Bank
Harmon.cpi.ger	Harmonized CPI, Germany	M	30	Eurostat
cpi.bw	Consumer Price Index, BW	M	0	Statistical Office of Baden-Württemberg
bpi.dwell.bw	Construction Price Index (dwellings), BW	Q	0	Statistical Office of Baden-Württemberg
bpi.offices.bw	Construction Price Index (offices), BW	Q	0	Statistical Office of Baden-Württemberg
cpi.ger	Consumer Price Index, Germany	M	30	Statistical Office of Baden-Württemberg
ppi.ger	Domestic producer prices—manufacturing, Germany	M	30	OECD
ppi.eu	Domestic producer prices—manufacturing, EU	M	30	OECD
<i>Labor market</i>				
unemp.bw	Unemployment rate, BW	M	5	Federal Employment Agency
unemp.ger	Unemployment rate, Germany	M	5	Federal Employment Agency
vacanc.ger	Vacancies, Germany	M	5	Federal Employment Agency
social.sec.ger	Employees subject to social security, Germany	M	60	Federal Employment Agency
total.employ.ger	Total domestic employment, Germany	M	30	Bundesbank
short.work.ger	Short-time work, Germany	M	0	Federal Employment Agency
earnings.h.ger	Negotiated hourly earnings, Germany	M	60	Deutsche Bundesbank
earnings.m.ger	Negotiated monthly earnings, Germany	M	50	Deutsche Bundesbank
constr.employ.bw	Employees in construction industry, BW	M	120	Federal Statistical Office
<i>Industries</i>				
indprod.ger	Industrial production, Germany	M	35	Bundesbank
turnover.industry.ger	Turnover industry, Germany	M	35	Bundesbank
orders.industry.ger	New orders in manufacturing industry, Germany	M	35	Deutsche Bundesbank
turnover.invest.ger	Turnover investment, Germany	M	35	Bundesbank
turnover.retail.ger	Turnover retail, Germany	M	45	Bundesbank
turnover.constr.ger	Turnover in construction, Germany	M	70	Federal Statistical Office
turnover.constr.bw	Turnover in construction, BW	M	70	Federal Statistical Office
constr.comp.bw	No. of companies in construction, BW	M	60	Federal Statistical Office
orders.constr.bw	New orders in construction, BW	M	70	Federal Statistical Office
orders.constr.ger	New orders in construction, Germany	M	55	Federal Statistical Office
industry.prod.eu	Industrial production excl construction, EU	M	60	Eurostat
industry.orders.eu	Industrial new orders, EU	M	60	European Central Bank
turnover.industry.eu	Manufacturing turnover, EU	M	90	Datastream
retail.sales.ger	Retail sales index excl cars, Germany	M	30	Deutsche Bundesbank
retail.sales.eu	Retail sales, EU	M	30	Eurostat
build.permit.eu	Building permits, EU	Q	105	Eurostat
build.permit.ger	Building permits, Germany	Q	105	Eurostat
constr.prod.eu	Industrial production construction, EU	M	60	Eurostat
car.reg.ger	New passenger car registrations, Germany	M	90	Federal Statistical Office
car.reg.eu	New passengers car registrations, EU	M	20	European Central Bank

Continues



TABLE C1 (Continued)

Variable	Description	Freq.	Min. Lag	Source
<i>International trade</i>				
exports.ger	Exports, Germany	M	60	Deutsche Bundesbank
imports.ger	Imports, Germany	M	60	Deutsche Bundesbank
import.eu	Import, EU	Q	70	European Central Bank
export.eu	Export, EU	Q	70	European Central Bank
<i>Financials</i>				
dax	DAX	M	0	Datastream
sp500	S&P 500	M	0	Datastream
eur.usd	Exchange rate EUR-USD	M	5	Deutsche Bundesbank
yield.debt.ger	Yield on all outstanding debt, Germany	M	5	Deutsche Bundesbank
euribor.eu	Euribor 3 months, EU	M	0	European Central Bank
brent.eu	Europe Brent spot price FOB, EU	M	20	US EIA
wti.us	WTI spot price FOB, US	M	0	US EIA
<i>Survey-based indicators</i>				
lbank.growthidx.bw	L-Bank growth index, BW	M	0	L-Bank
gfk.prices.bw	GfK price climate, BW	M	0	L-Bank
gfk.growth.bw	GfK economic climate, BW	M	0	L-Bank
gfk.income.bw	GfK income climate, BW	M	0	L-Bank
gfk.invest.bw	GfK investment climate, BW	M	0	L-Bank
gfk.consum.ger	GfK Consumer Climate Survey, Germany	M	0	GfK
ifo.industry.curr.ger	Assessment of the business situation: Manufacturing industry, Germany	M	0	ifo Institute
ifo.industry.exp.ger	Expect. with respect to business developments ( $t + 6$ ): manufacturing industry, Germany	M	0	ifo Institute
ifo.constr.curr.ger	Assessment of the business situation: construction industry, Germany	M	0	ifo Institute
ifo.constr.exp.ger	Expect. with respect to business developments ( $t + 6$ ): construction industry, Germany	M	0	ifo Institute
ifo.retail.curr.ger	Assessment of the business situation: Retail trade, Germany	M	0	ifo Institute
ifo.retail.exp.ger	Expect. with respect to business developments ( $t + 6$ ): retail trade, Germany	M	0	ifo Institute
ifo.wholesale.curr.ger	Assessment of the business situation: wholesale trade, Germany	M	0	ifo Institute
ifo.wholesale.exp.ger	Expect. with respect to business developments ( $t + 6$ ): wholesale trade, Germany	M	0	ifo Institute
ifo.trade.curr.ger	Assessment of the business situation: trade, Germany	M	0	ifo Institute
ifo.trade.exp.ger	Expect. with respect to business developments ( $t + 6$ ): trade, Germany	M	0	ifo Institute
ifo.export.ger	ifo export climate, Germany	M	30	ifo Institute
ifo.import.ger	ifo import climate, Germany	M	30	ifo Institute
ifo.manuf.bw	ifo business climate—manufacturing industry, BW	M	0	L-Bank
ifo.constr.bw	ifo business climate—construction industry, BW	M	0	L-Bank
ifo.wholesale.bw	ifo business climate—wholesale, BW	M	0	L-Bank
ifo.retail.bw	ifo business climate—retail, BW	M	0	L-Bank
retail.ci.ger	Retail confidence indicator, Germany	M	0	European Commission
services.ci.ger	Services confidence indicator, Germany	M	0	European Commission
building.ci.eu	Building confidence indicator, EU	M	0	European Commission
consumer.ci.eu	Consumer confidence indicator, EU	M	0	European Commission
industry.ci.eu	Industry—Business Climate Indicator, EU	M	0	European Commission
retail.ci.eu	Retail confidence indicator, EU	M	0	European Commission
services.ci.eu	Services confidence indicator, EU	M	0	European Commission
building.ci.ger	Building confidence indicator, Germany	M	0	European Commission
consumer.ci.ger	Consumer confidence indicator, Germany	M	0	European Commission
industry.ci.ger	Industry—Business Climate Indicator, Germany	M	0	European Commission
business.climate.eu	Business climate index, EU	M	0	European Central Bank
ZEW.short.ger	ZEW Indicator of Economic Sentiment (short term), Germany	M	0	ZEW
ZEW.long.ger	ZEW Indicator of Economic Sentiment (long term), Germany	M	0	ZEW

Note: The minimum publication lag is measured in days and counted from the end of the quarter/month to the date of the release. The 'Description' column contains information about whether the variable is available at a global, national, or regional resolution. Abbreviations: BW, Baden-Württemberg; CPI, Consumer Price Index; GDP, gross domestic product; OECD, Organisation for Economic Co-operation and Development.

TABLE C2 Descriptive statistics

Variable	AC1	AC2.	PAC2	Mean	Var
<i>GDP</i>					
gdp.bw	0.88	0.76	−0.07	0.39	1.36
gdp.ger	0.30	0.22	0.15	0.32	0.70
gdp.private.cons.ger	0.52	0.38	0.15	0.56	0.36
gdp.gov.cons.ger	0.69	0.54	0.11	0.33	0.06
gdp.invest.equip.ger	0.83	0.59	−0.35	0.20	0.34
gdp.invest.constr.ger	0.56	0.36	0.07	−0.03	0.21
gdp.gbr	0.52	0.36	0.12	0.49	0.40
gdp.nld	0.43	0.35	0.20	0.47	0.49
gdp.usa	0.22	0.09	0.05	0.49	1.43
gdp.ch	0.39	0.11	−0.06	0.44	0.43
gdp.fra	0.42	0.08	−0.12	0.19	2.68
<i>Money &amp; Prices</i>					
M2.eu	0.20	0.14	0.10	0.47	0.14
Harmon.cpi.eu	0.35	0.22	0.11	0.14	0.02
gdp.deflator.eu	0.23	0.12	0.07	−0.24	5.38
Harmon.cpi.ger	−0.08	0.12	0.11	0.12	0.04
cpi.bw	−0.09	0.08	0.07	0.12	0.04
bpi.dwell.bw	0.55	0.47	0.25	0.44	0.34
bpi.offices.bw	0.59	0.50	0.24	0.47	0.36
cpi.ger	−0.48	0.15	−0.11	0.12	0.16
ppi.ger	−0.02	−0.07	−0.07	−1.47	853.09
ppi.eu	0.54	0.30	0.01	0.09	0.21
<i>Labor market</i>					
unemp.bw	0.32	0.36	0.28	−0.01	0.01
unemp.ger	0.40	0.33	0.21	−0.01	0.01
vacanc.ger	0.74	0.57	0.05	0.18	4.74
social.sec.ger	0.74	0.64	0.22	0.08	0.02
total.employ.ger	0.56	0.33	0.02	0.05	0.02
short.work.ger	0.15	−0.22	−0.25	0.15	1119.90
earnings.h.ger	−0.48	0.02	−0.27	0.16	0.33
earnings.m.ger	−0.45	0.00	−0.25	0.16	0.16
constr.employ.bw	0.48	0.46	0.30	−0.11	0.40
<i>Industries</i>					
indprod.ger	−0.41	−0.01	−0.21	0.07	13.59
turnover.industry.ger	−0.34	−0.02	−0.16	0.13	13.06
orders.industry.ger	−0.05	−0.09	−0.09	0.13	13.72
turnover.invest.ger	−0.28	−0.11	−0.20	0.20	26.86
turnover.retail.ger	−0.48	−0.06	−0.38	0.12	2.69
turnover.constr.ger	−0.20	−0.02	−0.07	−0.10	25.17
turnover.constr.bw	−0.42	−0.05	−0.27	0.17	29.03
constr.comp.bw	0.08	0.07	0.07	−0.16	1.01
orders.constr.bw	−0.48	0.10	−0.17	0.15	150.30
orders.constr.ger	−0.50	0.10	−0.20	0.02	22.29
industry.prod.eu	0.16	−0.29	−0.33	0.04	3.86
industry.orders.eu	0.15	0.06	0.04	0.04	7.63
turnover.industry.eu	0.00	−0.08	−0.08	0.04	3.60
retail.sales.ger	−0.47	−0.10	−0.41	0.06	2.84
retail.sales.eu	−0.05	−0.37	−0.37	0.08	2.80
build.permit.eu	0.82	0.77	0.30	−0.69	15.93
build.permit.ger	−0.25	0.12	0.07	−0.72	89.90
constr.prod.eu	−0.27	−0.14	−0.23	−0.04	8.86
car.reg.ger	−0.19	0.00	−0.04	0.05	77.89
car.reg.eu	0.10	−0.35	−0.36	−0.09	120.02

Continues

TABLE C2 (Continued)

Variable	AC1	AC2	PAC2	Mean	Var
<i>International trade</i>					
exports.ger	0.05	−0.04	−0.04	0.14	22.38
imports.ger	−0.25	0.11	0.06	0.11	30.92
import.eu	0.48	0.25	0.04	1.05	3.27
export.eu	0.40	0.15	−0.01	1.03	4.21
<i>Financials</i>					
dax	0.04	0.03	0.03	0.54	35.45
sp500	−0.03	−0.06	−0.06	0.72	23.16
eur.usd	0.27	0.01	−0.07	−0.04	5.22
yield.debt.ger	0.36	0.07	−0.07	−0.02	0.02
euribor.eu	0.64	0.42	0.02	−0.02	0.02
brent.eu	0.23	−0.06	−0.13	0.30	112.15
wti.us	0.25	−0.04	−0.11	0.26	105.95
<i>Survey-based indicators</i>					
lbank.growthidx.bw	0.61	0.43	0.08	0.06	8.64
gfk.prices.bw	0.68	0.57	0.20	−0.10	8.10
gfk.growth.bw	0.80	0.66	0.04	0.07	11.90
gfk.income.bw	0.56	0.46	0.22	0.03	1.14
gfk.invest.bw	0.56	0.45	0.19	−0.02	2.03
gfk.consum.ger	0.24	−0.15	−0.22	−0.07	4.09
ifo.industry.curr.ger	0.48	0.36	0.17	−0.06	15.87
ifo.industry.exp.ger	0.43	0.01	−0.21	0.08	22.28
ifo.constr.curr.ger	0.03	0.08	0.08	0.25	7.15
ifo.constr.exp.ger	0.05	−0.08	−0.08	0.03	11.22
ifo.retail.curr.ger	−0.23	−0.14	−0.21	0.17	48.42
ifo.retail.exp.ger	0.02	−0.17	−0.17	−0.01	23.47
ifo.wholesale.curr.ger	−0.08	−0.03	−0.04	0.13	31.13
ifo.wholesale.exp.ger	0.15	−0.09	−0.12	0.05	25.17
ifo.trade.curr.ger	−0.10	−0.12	−0.13	0.15	27.34
ifo.trade.exp.ger	0.20	−0.15	−0.20	0.03	20.09
ifo.export.ger	0.19	0.12	0.09	0.00	0.06
ifo.import.ger	0.14	0.15	0.13	0.00	0.04
ifo.manuf.bw	0.26	0.18	0.11	−0.03	20.93
ifo.constr.bw	−0.21	−0.02	−0.06	0.19	16.65
ifo.wholesale.bw	−0.22	−0.03	−0.08	0.10	47.81
ifo.retail.bw	−0.24	−0.10	−0.17	0.09	52.44
retail.ci.ger	−0.08	−0.21	−0.22	0.05	17.16
services.ci.ger	0.15	−0.02	−0.04	−0.15	21.64
building.ci.eu	−0.03	−0.03	−0.03	0.07	5.56
consumer.ci.eu	0.15	−0.20	−0.22	−0.01	1.67
industry.bci.eu	0.36	0.05	−0.09	−0.01	4.85
retail.ci.eu	−0.07	−0.11	−0.11	0.02	9.05
services.ci.eu	0.28	−0.09	−0.18	−0.13	12.51
building.ci.ger	0.09	0.07	0.06	0.17	3.64
consumer.ci.ger	0.04	−0.09	−0.09	0.02	2.97
industry.bci.ger	0.39	0.23	0.09	0.01	5.81
business.climate.eu	0.40	0.30	0.16	0.00	0.04
ZEW.short.ger	0.31	0.12	0.02	0.21	145.90
ZEW.long.ger	0.53	0.33	0.07	−0.14	78.50

Note: The columns AC1 and AC2 contain the values of the autocorrelation function at the first and second lags, respectively. PAC2 denotes the partial autocorrelation function at the second lag (the first lag is identical to AC1). Mean and Var denote the sample mean and the sample variance, respectively.