IWH
Halle Institute for Economic Research
Member of the Leibniz Association

Discussion Papers

No. 24
December 2019

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IWH Discussion Papers are indexed in RePEc-EconPapers and in ECONIS.

Editor

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ISSN 2194-2188

Nowcasting East German GDP Growth: a MIDAS Approach*

Abstract

Economic forecasts are an important element of rational economic policy both on the federal and on the local or regional level. Solid budgetary plans for government expenditures and revenues rely on efficient macroeconomic projections. However, official data on quarterly regional GDP in Germany are not available, and hence, regional GDP forecasts do not play an important role in public budget planning. We provide a new quarterly time series for East German GDP and develop a forecasting approach for East German GDP that takes data availability in real time and regional economic indicators into account. Overall, we find that mixed-data sampling model forecasts for East German GDP in combination with model averaging outperform regional forecast models that only rely on aggregate national information.

Keywords: business surveys, East Germany, MIDAS model, nowcasting

JEL classification: C22, C52, C53, E37, R11

* This is a pre-print of an article published in Empirical Economics. The final authenticated version is available online at: https://doi.org/10.1007/s00181-019-01810-5. We would like to thank Klaus Wohlrabe and Robert Lehmann, the participants of the IWH-CIREQ-GW-Macroeconometric Workshop 2017 and of the 1. Vienna Workshop on Economic Forecasting 2018 and anonymous referees for helpful comments and suggestions. Research assistance by Franziska Exß is gratefully acknowledged.

1 Introduction

Economic forecasts are an important element of rational economic policy. In a federal state like Germany, not only aggregate macroeconomic projections but also forecasts on the state level are crucial. Government expenditures for infrastructure, for example, should reflect expected long-run regional economic developments. In the short run, high-quality forecasts of economic activity are important for the projection of future government revenues and solid budgetary planning. Although regional differences in tax revenues of the German states are largely smoothed by the fiscal transfer system, total revenues of the states and their municipalities also depend on the regional and local economic development. Furthermore, disaggregated macroeconomic projections can also improve aggregate tax forecasts. The German income tax is progressive, that is, the marginal tax rate depends on the income level. This implies that the effect of an increase in GDP by one Euro in a high-income state on federal tax revenues is larger than of the same increase of GDP by one Euro in a low-income state. In terms of GDP per capita, there are still relatively large differences between West and East German states. In 2018, GDP per capita was between 34 thousand Euro (Schleswig-Holstein) and 66 thousand Euro (Hamburg) in West Germany and between 28 thousand Euro (Mecklenburg-West Pomerania) and 31 thousand Euro (Saxony) in East Germany (without Berlin). GDP per capita in the "poorest" West German state is still larger than GDP per capita in the "richest" East German state. Moreover, GDP per capita lies in a much smaller range across East German states than across West German states. Therefore, we focus on regional GDP forecasts for East Germany as a whole. More specifically, we develop a forecasting approach for quarterly GDP in East Germany that combines existing aggregate forecasts for Germany with regional monthly indicators. However, the methodology can also be applied to the individual state level and to West Germany.

Since official statistics do not report quarterly GDP below the federal level, we provide a new quarterly time series for East German GDP, which can also be useful for further research. Even though East German GDP in general exhibits a similar pattern like aggregate GDP (Figure 1), there are periods with important deviations. For instance, in recent years, the growth rates of East Germany exceeded those observed for Germany as a whole, which can mainly be attributed to the rapid growth of the services sector in the area surrounding the German capital Berlin. Furthermore, since West Germany is more export oriented than East Germany, fluctuations in foreign demand show up stronger in West German GDP than in East Germany. During the Great Recession in course of the financial crisis 2008/2009, the decline and the subsequent recovery in aggregate German GDP were much more pronounced than in East Germany.

Although regional economic indicators should in principle help to forecast regional GDP, it is by far not clear whether this works in practice. Severe problems are data unavailability, low data publication frequency and substantial data revisions. Therefore, tracking and forecasting regional economic activity in Germany is a difficult task.[1] Only a few papers based either on bridge equations or factor models have so far tackled this issue by investigating macroeconomic developments at the regional level (e.g., Kopoin et al., 2013; Lehmann and Wohlrabe, 2014a, 2015; Henzel et al., 2015; Lehmann and Wohlrabe, 2017) or in countries with scarce data availability (see, e.g., Bragoli and Fosten, 2018). In our analysis, we focus on East Germany including Berlin.[2]

[1]For an general overview on obstacles in regional forecasting, see Lehmann and Wohlrabe (2014b).
[2]Other studies, e.g., Lehmann and Wohlrabe (2015), refer to East Germany excluding Berlin.

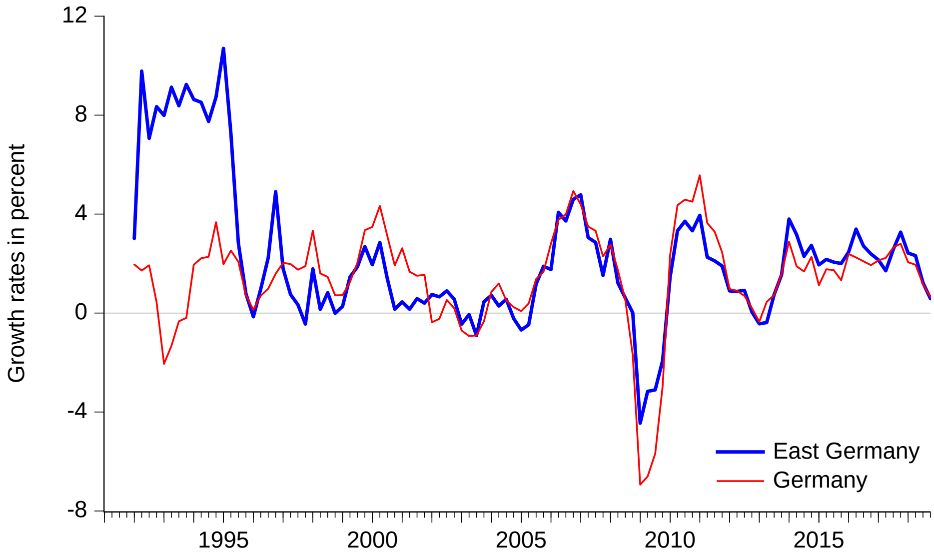


Figure 1: Quarterly East German real GDP and German real GDP

Quarterly real GDP growth compared to same quarter of the previous year.

Sources: German Federal Statistical Office and own calculations.

Our paper contributes to the literature on regional economic forecasting along several dimensions: First, we provide a new and unique quarterly time series of real GDP for East Germany from 1991 to 2018.[3] We will update this time series regularly in the future. Second, we explicitly mimic the ragged-edge data structure and consider several forecast rounds with different information sets within each quarter. Third, a natural concern is whether forecasts based only on nation-wide indicators already comprise all relevant information needed to monitor regional economic growth. If this is not the case, nation-wide forecasts might be either not efficient or regional factors determining (regional) GDP growth might indeed contain additional information not included in nation-wide factors. Thus, we analyze whether aggregate forecasts are already efficient for regional forecasting and investigate whether regional information further improves the forecasts. To this end, we present a mixed-data sampling (MIDAS) approach to nowcast current quarter East German real GDP growth using monthly business cycle indicators for East Germany at different forecast rounds. More specifically, our model takes into account past quarterly East German real GDP growth, contemporaneous and past quarterly German real GDP growth and monthly business cycle indicators for East German states. Given that *ex post* real GDP data for Germany are not available in real time, we include a publically available nowcast for current quarter real GDP growth for Germany published by the Halle Institute for Economic Research (IWH) instead of the actual value into our forecasting model for East Germany. Overall, we find that MIDAS model forecasts for East German GDP in combination with model averaging outperform regional forecast models that only rely on aggregate information.

The paper is structured as follows: Section 2 presents the data used in the analysis, explains the construction of quarterly East German GDP and discusses its link to total German GDP growth. In addition, regional monthly business cycle indicators are described. In Section 3, we present our benchmark models and selected MIDAS models used in the statistical analysis. In Section 4, we document the forecasting performance of the MIDAS models in relation to the optimal versions of the benchmark models. Section 5 concludes.

[3]Data are available at `https://www.iwh-halle.de/en/research/data-and-analysis/macroeconomic-reports/macro-data-download/`

2 Data

2.1 East German GDP

GDP is a key indicator for the analysis and monitoring of regional economic development. The main data source for GDP at regional level is the releases of a working group formed by the statistical offices of the federal states on regional accounts (Arbeitskreis Volkswirtschaftliche Gesamtrechnungen/ working group “Regional Accounts”). Based on gross value added calculations, recent GDP figures are only available at annual frequency and are published with a delay of three months after the end of the reference period. Updates for the first half of a year are published in the summer of the corresponding year. The working group has stopped producing quarterly data for the time after 1999. However, the IWH provides quarterly data for East German GDP (with and without Berlin). We apply temporal disaggregation, benchmarking and reconciliation methods to the official annual and semiannual data for East Germany in order to compute quarterly GDP. Below, we describe the general approach and a detailed description is provided in the Appendix A.

For the calculation of East German GDP (including Berlin), we start by using official statistics published by the German Federal Statistical Office for the period 1991–1994. These comprise quarterly GDP as well as gross value added for East German states. For the period 1995–2015, the quarterly shares are based on a bottom-up-approach (based on gross value added components). For the period since 2016, we use monthly indicators to temporally disaggregate the annual series. This procedure is complicated by the fact that official regional statistics for monthly and/or quarterly indicators are rare and only published with some delay. We use the ECOTRIM package provided by Eurostat that implements the Chow and Lin (1971) method for temporal disaggregation of time series. This econometric approach captures the relationship between indicators and the target variable very well. Currently, the number of employees contributing to the social security system and turnover in manufacturing are the most important indicators for the quarterly breakdown. In line with the European Statistical System (ESS) guidelines on temporal disaggregation, benchmarking and reconciliation techniques, the data are seasonally adjusted by using the X-12-ARIMA procedure after disaggregation.

2.2 Nowcast for total German GDP

Figure 1 shows that the correlation pattern between total German GDP and East German GDP is high after 1995. Hence, business cycle dynamics did not differ significantly from those in West Germany – if the overall economy is considered. However, due to different sectoral patterns, up- and downswings can deviate from turning points for Germany with regard to their magnitude. For instance, while East Germany was less affected by the downturn during the Great Recession, the recovery was less pronounced as well. Overall, synchronization of business cycles in East and West Germany has increased significantly (Gießler et al., 2019).

For the above-mentioned reasons, we take the economic development in Germany into account for nowcasting East German GDP.[4] Seasonally adjusted real quarterly GDP growth rates published by the German statistical office are used. A major problem is that GDP data are released with a delay of 1.5 months after the reference period. Hence, in a real-time nowcasting framework, neither German nor East German data are available for the previous quarter when we start our nowcast exercise for East German GDP growth. To circumvent this issue, we make use of quarterly IWH forecasts that are published every quarter. On the one hand, we analyze the power of the IWH-flash-indicator that provides a nowcast for German GDP growth for the current quarter and is available right after the publication of German GDP

[4]In this paper, we use the terms nowcasting and forecasting similarly, both referring to the current quarter.

for the previous quarter.[5] This indicator is available since 2011. On the other hand, we also use quarterly IWH forecasts that might deviate slightly from the IWH-Flash-indicator because they incorporate further information on the current quarter. Forecast evaluation statistics show that IWH's GDP nowcasts are neither biased nor distorted and forecast errors do not reveal serial correlation (Table 5).

2.3 Business cycle indicators for East Germany

As far as monthly indicators are concerned, only a few regional series are available in a timely manner. We were able to collect 23 headline indicators comprising sectoral and aggregate information on the East German economy. On the one hand, we incorporate into our analysis ifo survey data on the situation, expectations and climate in manufacturing, construction, retail trade, wholesale trade, and trade and industry sectors. In addition, we consider survey data on capacity utilization in the construction sector.[6] On the other hand, we make use of hard indicators like new orders in manufacturing, turnover in manufacturing, new orders in construction, turnover in construction, unemployment rate, vacancies and employees contributing to the social security system.[7] All indicators are seasonally adjusted and are converted to be stationary by applying first differences or growth rates, respectively. For more details on the indicators used in the analysis, see Table 4 in the Appendix B.[8] To circumvent the problem of regional data availability, additional national and international indicators could be used (Lehmann and Wohlrabe, 2015). Hence, for robustness, we additionally use German indicators; however, we do not expect any significant gains as we already take into account the GDP measure for the whole German economy and we assume that this nowcast figure already contains sufficient information on the national level. In addition, we make use of growth differences between the East German indicator and the corresponding German one to remove nation-wide variation.

3 Nowcasting framework

In this section, we present the nowcasting setup and the different models specified in the paper. All models presented below are estimated at the end of each month including newly released information. We mimic the real-time environment for the nowcasting exercise (Figure 2), focusing on three different forecast rounds (F1, F2, F3) for a specific quarter. Forecast round F1 takes place after the publication of German GDP data ($Germany$) for the previous quarter and after the release of the second month for selected indicators, round F2 after the publication of the regional GDP data ($East\ Germany$) and several indicator data for the third month, and finally round F3 in the month before the release of the respective national quarter. Given that real-time data are neither published for GDP nor for indicators at the regional level, we use final data and constrain the analysis to the exact timing of data availability. In Figure 2, the availability of indicators is shown in detail for the first quarter of a year; however, the indicators used are available in monthly frequency, and hence, they are available for all other quarters respectively. A peculiarity is that in the first (and third) quarter of the year, East German GDP data are not available for the previous two periods in forecast round F1. However, from forecast round F2 onward, regional GDP data is available for the previous quarter. In contrast, in the second (and fourth) quarter, regional GDP information is not available at all for the previous two periods for all forecast rounds. Updates for regional GDP growth in the first half of the year are published in the summer.

[5] See IWH-flash-estimate: `http://www.iwh-halle.de/en/research/data-and-analysis/macroeconomic-reports/iwh-flash-indicator/`

[6] A drawback of the ifo survey data for East Germany is that they do not include Berlin.

[7] In contrast to Lehmann and Wohlrabe (2017), we also take the indicators into account that are used for disaggregation of annual data to see whether there are information advantages.

[8] To make the indicators comparable to GDP, we report them in quarterly frequency in the figures.

Figure 1 provides evidence that GDP growth rates after the German reunification have been very different in East and West Germany in the initial catching-up period. Therefore, our sample period covers 1996Q1–2018Q4. All models are initially estimated from 1996Q1–2010Q4 and are recursively estimated with rolling window size until 2018Q4. Thus, we end up with 32 forecasts to evaluate.

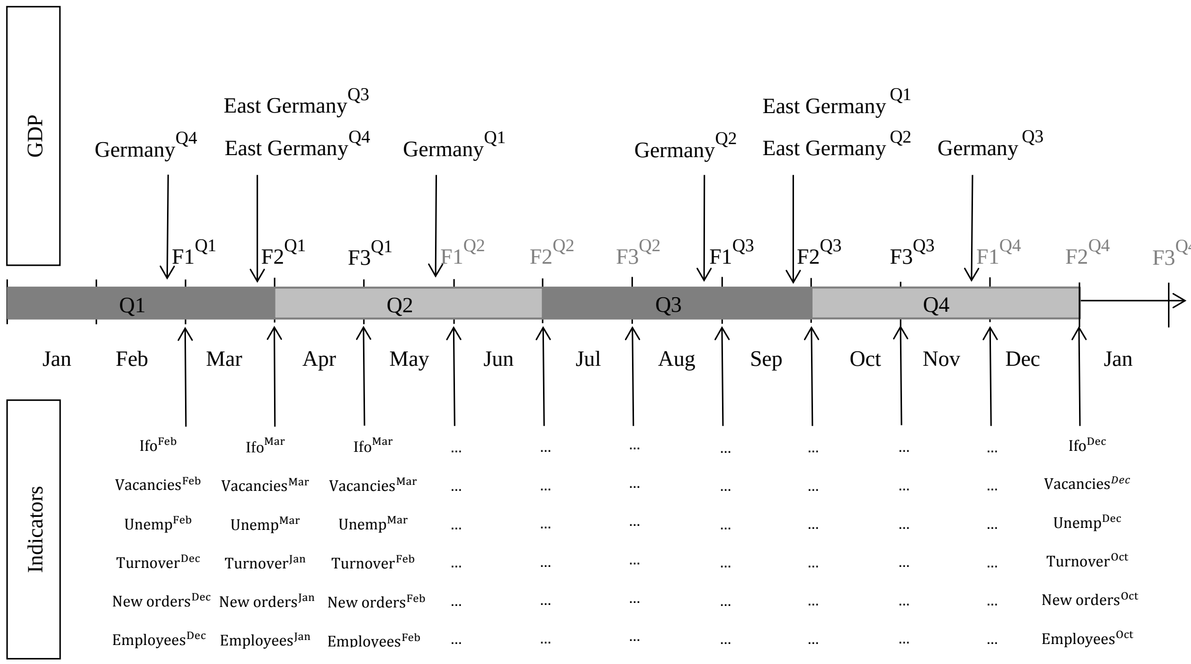


Figure 2: Real-time data flow

With respect to the availability of monthly East German indicators and quarterly East German and German GDP data, different forecast rounds are labeled with F1, F2, F3.

To assess the performance of the indicator-based models, we implement standard benchmark models. The first benchmark model is an autoregressive (AR) model, for which the optimal lag length i is determined according to the Akaike information criterion (given the availability of ex-post data k):

$$y_t = \alpha_0 + \sum_{i=k}^{p} \alpha_i y_{t-i} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon), \tag{1}$$

where y_t is the quarterly East German real GDP growth rate. Furthermore, we use a historical mean model as a benchmark without any other information.

Another benchmark model used is based on a bivariate dynamic regression (ARDL models), for which we establish two different scenarios: First, we propose the inclusion of the corresponding IWH (flash) forecast of the current quarter for Germany as a solution to the nonexistence of contemporaneous data. Second, we take an *idealistic, however unpractical* case where Germany's real GDP growth rates are assumed to be known contemporaneously, i.e., *ex post data*. Our ARDL model containing total German growth rates is defined as follows:

$$y_t = \alpha_0 + \sum_{i=k}^{p} \alpha_i y_{t-i} + \sum_{j=0}^{q} \beta_j x_{t-j} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_\varepsilon), \tag{2}$$

where we augment the above described autoregressive model by x_t denoting (the forecast for) German real GDP growth. The optimal lag length for j and i is also determined according to the Akaike information criterion.

Given the availability of monthly East German business cycle indicators, we implement the MIDAS approach in order to explore the data available at a higher frequency and to infer any relevant information on the East German business cycle. In this regard, our regional MIDAS regression models take the following form:

$$y_t = c + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=0}^{q} \beta_j x_{t-j} + \gamma B(L^{(1/m)}; \theta) z_t^{(m)} + \epsilon_t^{(m)} \tag{3}$$

where $B(L^{(1/m)}; \theta) = \sum_{k=0}^{K} B\left(k; \theta\right) L^{(k/m)}$ is the weighting scheme used for aggregation and $L^{(1/m)}$ is the lag operator such that $L^{(1/m)} z_t^m = z_{t-1/m}^m$. K is the number of lags for the indicators. m reflects the higher sampling frequency (m = 3 for monthly data). During a specific quarter, three forecasts $\hat{y}_{t+h}$ can be conducted using $z_t^{(m)}$. As far as the MIDAS approach is concerned, we implement the methodology along the lines of the work by Ghysels et al. (2004), Ghysels et al. (2006) and Ghysels et al. (2007). For a more practical point of view, we also refer to the work by Clements and Galvão (2008) and Armesto et al. (2010). As for the application of MIDAS models to the case of Germany and also the Euro Area, we refer to the contributions by Marcellino and Schumacher (2010) and Kuzin et al. (2011). Given that we explore monthly indicators in order to obtain information on a quarterly variable, we also test, in addition to the commonly used (exponential) Almon lag distribution, an unrestricted version of the MIDAS model as proposed by Foroni et al. (2015). The intuition behind this approach is that the range from month to quarter is not that large, so that the (exponential) Almon weighting scheme might be inappropriate for such a short shift in frequencies.

Following the contribution by Andreou et al. (2013), we consider one monthly indicator in the MIDAS regression at a time so that, in the end, we are left with 18 indicator models in forecast round F1 and 23 models in forecast rounds F2 and F3, respectively. Considering more than one monthly regressor might lead to multicollinearity issues and a rapid increase in the number of coefficients to be estimated.

Furthermore, the literature has shown that forecast averaging could improve the forecast performance significantly (for Germany, see, for example, Drechsel and Scheufele, 2012; Heinisch and Scheufele, 2018). Therefore, we provide a forecast averaging exercise based on several weighting schemes (Timmermann, 2006): (i) The easiest approach takes the simple arithmetic mean of the forecasts at each observation in the forecast sample; hence, every indicator-based forecast is given the same weight. (ii) If we exclude the highest 5% and the lowest 5% of the forecast values (Stock and Watson, 2004), the trimmed mean can be calculated at each observation, which implies that the weights assigned to each indicator-based forecast are time varying. (iii) The simple median approach is based on the median of the indicator-based forecasts. In addition, we make use of the pseudo out-of-sample fit of the indicator-based forecasts and apply weights based on (iv) mean squared errors (MSE). This approach yields a weight based on the ratio of each forecast's MSE to the total of all the MSEs and implies that those models obtain greater weights which were more accurate in the past. We take into account all MSEs in the past instead of restricting the MSE to a subset of forecast errors only. Rather than computing the ratio of MSE values, (v) MSE rank weighting ranks the MSE of each forecast, i.e., it uses the ratio of the inverse of the ranks. Hence, each forecast's weight corresponds to its rank divided by the sum of all ranks.

4 Forecast performance

In this section, we analyze the forecast errors of the quarterly estimates for East German GDP and compare the forecasting performance to an optimal AR model, bivariate models including German quarterly GDP growth and various MIDAS models.

4.1 Evaluation methods

In order to evaluate the performance of the models, we estimate them from 1996Q1 to 2010Q4 and then produce forecasts by using a rolling window for the new upcoming information to be considered in the estimation. A shorter window may be more robust to structural breaks, but might not provide as precise estimates as larger windows (Rossi and Inoue, 2012).

Forecasts for East German GDP growth are conducted for the three different forecast rounds for a specific quarter reflecting the flow of conjunctural information in line with the availability of monthly data for the respective quarter. The first nowcast is produced for 2011Q1. By rolling the estimation sample until 2018Q3, the final nowcast is produced for 2018Q4.

Forecast errors in the evaluation period 2011–2018 are measured by squared loss functions, either by mean squared forecast errors (MSFE) or root mean squared forecast errors (RMSFE). Since those forecast errors are difficult to interpret, indicator-based forecasts of the MIDAS estimations are compared with those of univariate time-series models (Granger and Newbold, 1977; Stock and Watson, 2003). This provides us with information on how much a leading indicator-based forecast is better than the benchmark where no further information is specified (in percentage points).

$$relative\ RMSFE = \frac{\sqrt{\sum_{t=T_1}^{T_2} \left(\widehat{y}_t^i - y_t\right)^2}}{\sqrt{\sum_{t=T_1}^{T_2} \left(\widehat{y}^{AR} - y_t\right)^2}} = \frac{\sqrt{\sum_{t=T_1}^{T_2} \left(\widehat{e}_t^i\right)^2}}{\sqrt{\sum_{t=T_1}^{T_2} \left(\widehat{e}_t^{AR}\right)^2}}, \tag{4}$$

where $\widehat{y}_t^i$ is the GDP forecast based on indicator i for period t. The corresponding forecast error is defined by the difference between the forecasts and the realization y_t ($\widehat{e}_{i,t} = \widehat{y}_t^i - y_t$). Similarly, $\widehat{y}_t^{AR}$ is the pure AR-forecast and $\widehat{e}_t^{AR}$ the corresponding forecast error. T_1 indicates the first date of the pseudo out-of-sample forecast and T_2 the date where the last forecast is observed. Whenever the average performance of the indicator-based forecast is better than the AR forecast, the relative RMSFE is smaller than one.

However, the pure RMSFE (or relative RMSFE) measure provides no evidence on whether the difference is statistically significant. A more formal test procedure is necessary to decide which models to be preferred. To evaluate whether an indicator-based forecast is systematically better than the benchmark, we apply statistical tests of equal predictive ability. One popular test for this hypothesis is the Diebold–Mariano test of equal predictive ability (Diebold and Mariano, 1995). However, this test is only valid for comparing pure forecasts and not forecasting models (Diebold, 2015). In addition, the comparison of forecast errors involves models with estimated parameters, and inference on these models may be complicated, particularly when models under investigation are nested (see West, 1996). Since we have chosen a rolling window, we may occasionally select different models, and hence, we might evaluate forecasts that are combinations of nested and non-nested models. Therefore, we make use of the test on unconditional predictive ability test proposed by Giacomini and White (2006). This framework makes it possible to compare forecasts from different models and different modeling procedures like model averaging schemes. The test of equal unconditional predictive ability relies on $H_0:\ E\left[(\widehat{y}_t^i - y_t)^2 - (\widehat{y}_t^{\mathbf{AR}} - y_t)^2\right] = 0$.

The test statistic is

$$Z^i_= \frac{(T_2 - T_1)^{-1} \sum_{t=T_1}^{T_2} \left[(\widehat{y}_t^i - y_t)^2 - (\widehat{y}_t^{AR} - y_t)^2\right]}{\hat{\sigma}/\sqrt{T_2 - T_1}} \tag{5}$$

where the average loss differential is divided by the standard error. $\hat{\sigma}^2$ is a HAC estimator of the asymptotic variance. The test statistic Z^i follows an asymptotically normal distribution under the assumption that the difference in squared forecast errors is covariance stationary.

For our benchmark models, we test for unbiasedness by regressing the forecast error on a constant ($\widehat{e} = \alpha + \epsilon$) and test the null $H_0 : \alpha = 0$. Furthermore, we test for efficiency using the Mincer–Zarnowitz test based on the regression $y_t = \alpha + \beta\widehat{y}_t^i + \epsilon$ and test the null $H_0 : \alpha = 0, \beta = 1$. Finally, we test the null of no serial correlation in forecast errors using the Ljung–Box Q-statistics and their corresponding p-values.

4.2 Performance of benchmark models

This section presents the results for nowcasting regional GDP growth. First, the AR(p)-model is commonly used as benchmark model and all other suggested benchmark models are compared to the results of the AR-benchmark. In general, we find that forecasts are systematically unbiased and efficient, and forecast errors indicate no serial correlation at the 5% percent level.[9] The ARDL model including the IWH forecast yields the lowest forecast error. This can be also confirmed for all forecast rounds (Table 1). In addition, there is almost no difference between the optimal AR(p) model and a simple mean forecast based on past values. The benchmark model (ARDL opt + true GDP) considering the case, in which Germany's real GDP growth rates are assumed to be known contemporaneously, provides the best results (improvement of 22%) and is significantly different. However, we have to keep in mind that this model is an *idealistic*, but *unrealistic* solution. The practical version of the model (ARDL opt + IWH forecast) described above proposes the substitution of *ex post* data by forecasts published by the IWH for current quarter GDP growth. This model also provides significant results with an improvement of 12–15% compared to the benchmark. Although the results described above hold for all forecast rounds, the forecast errors do not necessarily decrease from forecast round F1 to F2 – as one would typically expect.[10]

Table 1: Forecast evaluation statistics for benchmark models

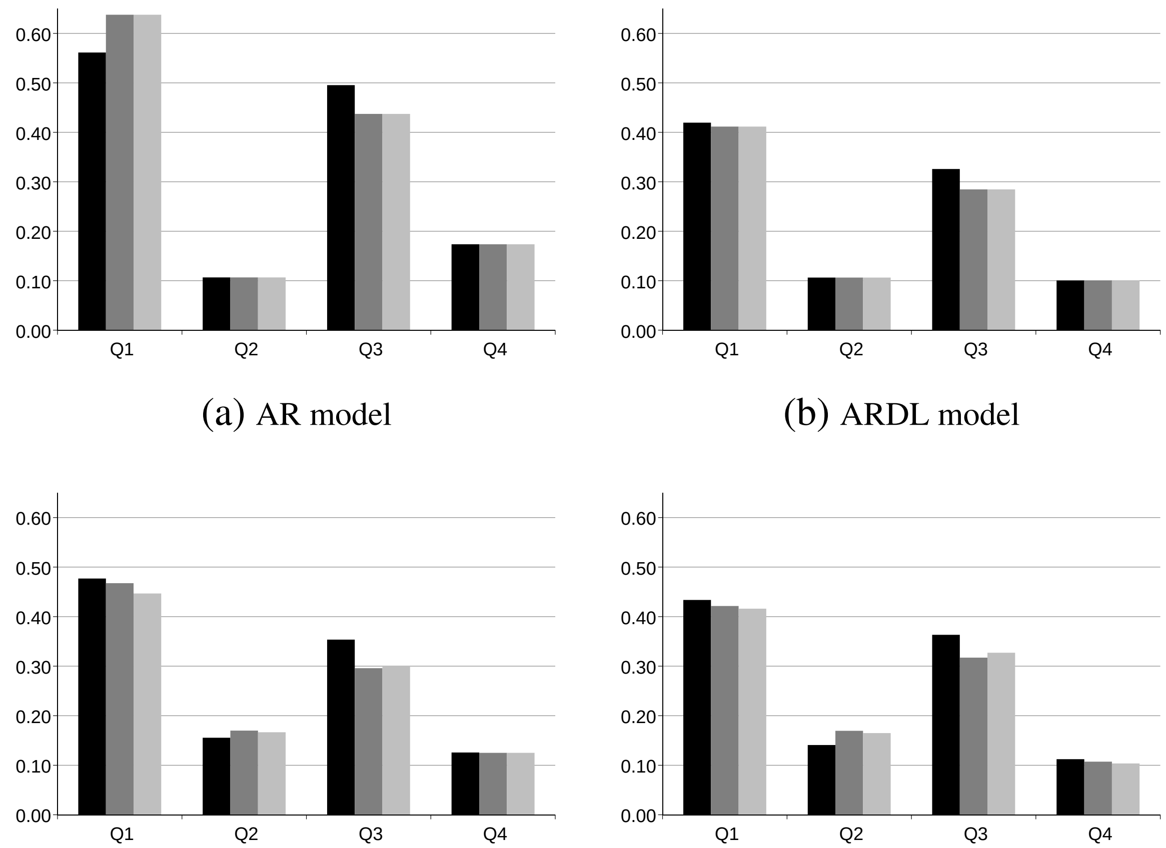
	F1	F2	F3
AR opt (RMSFE)	0.555	0.559	0.559
ARDL opt	0.920	0.903**	0.903**
Mean forecast	0.968	0.962**	0.962**
ARDL opt + IWH Forecast DE	0.879 **	0.849***	0.849***
ARDL opt + IWH Flash Forecast DE	0.964	0.933	0.933
ARDL opt + TRUE GDP DE	0.788 **	0.781***	0.781***

The RMSFE of the AR-model is given in the first row. Relative RMSFEs for all other benchmark models and indicator-based models are given and compared to the benchmark AR-model. ***, ** and * indicate whether the forecast ability is significant at the 1%, 5% and 10% level, respectively.

This result shows the shortcoming of the data availability of regional GDP — published only twice a year. It implies that the quarterly information remains the same during the forecast rounds in the second and fourth quarter, respectively (Figure 3a,b). Minor differences occur from forecast round F1 to F2 for nowcasts conducted for the first and the third quarter. But due to the consideration of the entire evaluation period, this effect almost disappears. If the quarters are analyzed separately, there is clear evidence that

[9]Table 6 provides an overview of the forecasting properties of our benchmark models.
[10]In forecast round F2 and F3, the same benchmark models are used.

nowcasts for the first and third quarter feature the greatest forecast errors. For the second quarter, the mean squared forecast error is comparatively low.



(a) AR model

(b) ARDL model

(c) MIDAS model

(d) UMIDAS model

Figure 3: Quarterly forecast errors

Mean squared forecast errors are shown for each quarter in percentage points. Different forecast rounds are labeled with F1 (black bar), F2 (dark gray bar) and F3 (light gray bar). The ARDL-models include the IWH forecast for the current quarter.

4.3 Indicator results

In the previous subsection, we have shown that using current quarter real German GDP information helps predicting East German GDP growth. However, regional indicators might improve the forecast for East German GDP growth because there are regional factors not included in the IWH forecast for Germany. Therefore, we analyze to what extent monthly regional data based on business surveys and hard data further improve the predictive ability of the (best performing) benchmark model. In addition, nation-wide variation is removed from regional indicators by subtracting the respective nation-wide indicators.

Table 2 provides evidence that some regional indicators for East Germany are useful to improve the benchmark AR-model. By applying the mixed frequency data sampling methodology, we find that the restricted class of MIDAS models encompassing monthly information on, e.g., the situation and expectations in the construction, manufacturing and trade sectors, capacity utilization in construction and vacancies, significantly improves the forecasting ability of the models in almost all three forecast rounds. MIDAS models containing those monthly indicators are able to improve the forecast performance up to

18 %. The same holds true for the respective MIDAS-models with (total) German monthly indicators. As for the models considering growth differences, the climate in manufacturing, situation and expectations in retail trade sector provide further forecasting improvements. It turns out that East German indicators perform in more than 60 % of the cases better than their total German counterparts and about 80 % better than their respective growth difference to total Germany. However, using the growth differences between East and total German indicators also increases the performance compared to only using the total German indicator. Overall, about 25 % of the indicator-based forecasts are significantly better than the benchmark in forecast round F1 and about 65 % in rounds F2 and F3, respectively.

The best performance is achieved during forecast round F2 by the MIDAS regression containing the climate in retail trade and is, therefore, the closest we can get to the idealistic case of observing Germany's real GDP growth rates contemporaneously. However, the inflow of new monthly information — in particular between forecast rounds F2 and F3 — does not contribute to the increase in the performance of the MIDAS models (see also Figure 6 in Appendix B). This is in line with previous regional nowcasting analyses (Henzel et al., 2015) who find that the performance of regional GDP forecasts is similar across different information sets within a quarter. Furthermore, our results are also stable for all quarters (Figure 3c). Furthermore, in the second and fourth quarter of a year, MIDAS-models cannot enhance ARDL models (including IWH-nowcasts for Germany).

As for the unrestricted case of MIDAS regressions (see Table 3, Figure 3d), we find consistent and robust evidence in favor of the indicators measuring the climate in manufacturing and the current situation, expectations and climate in retail trade, in all three different setups. In addition, the indicators on the capacity utilization in construction and vacancies provide significant results. Overall, the performance of UMIDAS-models is similar to those of the MIDAS models. By analyzing the quarterly nowcasts separately, we find that UMIDAS-models can outperform MIDAS-models only in the fourth quarter.

Overall, our results are comparable to previous findings in the literature using boosting techniques with improvements by indicators up to 20 % (Lehmann and Wohlrabe, 2017), where indicators such as vacancies, production in construction sector and retail sales are also among the most promising indicators.[11] Given that forecasts based on the optimal ARDL-model including the IWH-forecast have already provided reasonable improvements compared to the ARDL-forecast, the natural question arises, whether regional indicators might still be able to beat these results. Hence, if the indicator-based forecasts are directly compared to those of the ARDL-model, it turns out that only expectations in retail trade can significantly improve the benchmark ARDL-model up to 5 %. Expectations in manufacturing and construction also slightly improve the ARDL-forecasts. Similarly, as a further robustness analysis we estimate the model in eq.(2) by using the true GDP for the growth rate of German GDP and compare the results to the respective benchmark with true GDP. Although some indicators provide improvements, they are no longer statistically significant.

[11] They consider quarterly year-on year forecasts for the sample 1997–2013.

Table 2: Forecast evaluation statistics for MIDAS models compared to AR model

	with East indicators			with German indicators			with East-Total Diff		
	F1	F2	F3	F1	F2	F3	F1	F2	F3
Indicator models									
situation in construction	0.954	0.893**	0.893**	1.058	1.038	1.038	0.932	0.893	0.893
expectations in construction	0.918*	0.831**	0.831**	0.964	0.902	0.902	0.944	0.916**	0.916**
climate in construction	0.894	0.831	0.831	0.964	0.941	0.941	0.964	0.860	0.860
situation in manufacturing	1.038	0.925***	0.925***	1.084	1.000	1.000	0.961	0.926*	0.926*
expectations in manufacturing	0.948	0.847*	0.847*	0.970	0.880	0.880	0.944	0.903	0.903
climate in manufacturing	1.004	0.918**	0.918**	1.049**	0.948***	0.948***	0.973*	0.952***	0.952***
situation in retail trade	0.876**	0.838***	0.838***	0.883**	0.791***	0.791***	0.915**	0.818**	0.818**
expectations in retail trade	0.870**	0.810***	0.810***	0.866*	0.817***	0.817***	0.855*	0.869***	0.869***
climate in retail trade	0.885	0.794**	0.794**	0.928	0.790**	0.70**	0.891	0.816	0.816
situation in wholesale trade	0.934	0.852	0.852	0.936**	0.829***	0.829***	0.961	0.991	0.991
expectations in wholesale trade	0.956	1.068	1.068	0.877	0.838**	0.838**	0.968	1.019	1.019
climate in wholesale trade	0.987	1.043	1.043	0.938	0.861	0.861	0.958	1.067	1.067
situation in trade & industry	1.020	1.013	1.013	1.020	0.958**	0.958**	0.939	0.965*	0.965*
expectations in trade & industry	0.869	0.876*	0.876*	0.980	0.853**	0.853**	0.944	0.910	0.910
climate in trade & industry	0.961	0.913	0.913	1.013	0.897	0.897	0.907	0.993	0.993
capacity utilization	0.915**	0.896**	0.896**	0.939**	0.948**	0.948**	1.034	0.950**	0.950**
vacancies	0.867**	0.874**	0.874**	0.871*	0.860***	0.860***	0.915*	0.878*	0.878*
unemployment rate	0.881	0.844*	0.844*	0.907	0.851	0.851	0.869**	0.872**	0.872**
employees contributing to social security		0.895*	0.864*		0.911	0.931		0.853*	0.831*
turnover, manufacturing		0.900	0.895		0.925	0.919		0.905	0.889
new orders, manufacturing		1.005*	0.966*		0.919	0.988		0.915	0.968
new orders, construction		0.900*	0.885		1.554	1.257		1.087	1.245
turnover, construction		0.911	0.916*		0.907	0.891		0.896	0.965
Forecast combinations									
mean	0.889**	0.857**	0.850	0.920*	0.866**	0.850	0.872**	0.859**	0.870
trimmed mean		0.855**	0.85**		0.855***	0.860***		0.857**	0.860**
median	0.876**	0.855**	0.850**	0.900**	0.836***	0.850***	0.874**	0.850***	0.850**
mse	0.884**	0.850**	0.840**	0.913*	0.851***	0.850***	0.870**	0.851**	0.850**
ranks	0.866**	0.830***	0.820***	0.892**	0.832***	0.830***	0.857**	0.836***	0.840**

Relative RMSFEs for all indicator-based models are given and compared to the benchmark AR-model. ***, ** and * indicate whether the forecast ability is significant at the 1%, 5% and 10% level, respectively.

Table 3: Forecast evaluation statistics for U-MIDAS models compared to AR model

	with East indicators			with German indicators			with East-Total Diff		
	F1	F2	F3	F1	F2	F3	F1	F2	F3
Indicator models									
situation in construction	1.006	0.938**	0.938**	0.960	0.983**	0.983**	0.996	0.842	0.842
expectations in construction	0.950*	0.858**	0.858**	0.885	0.882	0.882	0.968	0.842**	0.842**
climate in construction	0.908	0.894	0.894	0.919	0.930	0.930	0.971	0.862	0.862
situation in manufacturing	0.967	0.934***	0.934***	0.996	0.957**	0.957**	0.940	0.886*	0.886*
expectations in manufacturing	0.850	0.832*	0.832*	0.893	0.876	0.876	0.922	0.879	0.879
climate in manufacturing	0.880**	0.853**	0.853**	0.938**	0.895***	0.895***	0.915*	0.888***	0.888***
situation in retail trade	0.909**	0.868***	0.868***	0.9**	0.837***	0.837***	0.930**	0.828**	0.828**
expectations in retail trade	0.906**	0.879***	0.879***	0.895*	0.84***	0.84***	0.940*	0.917***	0.917***
climate in retail trade	0.914	0.867**	0.867**	0.901	0.835**	0.835**	0.920	0.858	0.858
situation in wholesale trade	0.929	0.875	0.875	0.976**	0.854***	0.854***	0.934	0.938	0.938
expectations in wholesale trade	0.957	1.106	1.106	0.900	0.805**	0.850**	0.963	1.059	1.059
climate in wholesale trade	0.985	1.057	1.057	0.956	0.852	0.852	0.981	1.033	1.033
situation in trade & industry	0.942**	0.970**	0.970**	0.974	0.937**	0.937**	0.927	0.887*	0.887*
expectations in trade & industry	0.860	0.848*	0.848*	0.896	0.861**	0.861**	0.939	0.844	0.844
climate in trade & industry	0.906	0.896	0.896	0.947	0.881	0.881	0.899	0.858	0.858
capacity utilization	0.956**	0.821**	0.821**	0.943**	0.882**	0.882**	1.024	0.872**	0.872**
vacancies	0.907**	0.845**	0.845**	0.863*	0.859***	0.859***	0.912*	0.866*	0.866*
unemployment rate	0.868	0.862*	0.862*	0.930	0.850	0.850	0.852**	0.861**	0.861**
employees contributing to social security		0.890*	0.867*		0.892	0.857		0.867*	0.846*
turnover, manufacturing		0.908	0.896		0.911	0.866		0.893	0.908
new orders, manufacturing		0.868*	0.851*		0.883	0.891		0.877	0.877
new orders, construction		0.881*	0.873		1.371	1.228		1.110	1.098
turnover, construction		0.882	0.929*		0.890	0.884		0.922	1.063
Forecast combinations									
mean	0.895**	0.859**	0.860	0.902*	0.865**	0.850	0.893**	0.847**	0.860
trimmed mean		0.857**	0.850**		0.857***	0.850***		0.840**	0.850**
median	0.89**	0.848**	0.850**	0.906**	0.855***	0.850***	0.898**	0.842***	0.840**
mse	0.892**	0.853**	0.850**	0.900*	0.854***	0.850***	0.891**	0.834**	0.840**
ranks	0.878**	0.834***	0.830***	0.888**	0.84***	0.840***	0.881**	0.821***	0.820**

Relative RMSFEs for all indicator-based models are given and compared to the benchmark AR-model. ***, ** and * indicate whether the forecast ability is significant at the 1%, 5% and 10% level, respectively.

4.4 Forecast combination

In terms of the model averaging exercise based on a simple mean, trimmed mean, simple median, mean squared error and mean squared error ranks, we find statistically significant results. In the restricted MIDAS case, the averaged results in forecast round F1 are clearly better than almost all models containing monthly indicators. Only MIDAS models considering the situation in the retail trade sector or vacancies perform better than the forecast average. In forecast round F2, information on the situation, expectations and climate in the retail trade sector of East Germany and the situation in the wholesale trade sector proves to be better than the results under model averaging. A similar pattern emerges for the average of MIDAS-models based on the respective growth differences.

As for the unrestricted MIDAS case, only information on the expectations in manufacturing is able to perform better than the model averaging during forecast round F1. In forecast round F2, only the models considering the situation, expectations and climate in retail and wholesale trade seem to outperform the model averaging approach as well.

Overall, we can confirm previous findings in the literature for East German GDP forecasts (Lehmann and Wohlrabe, 2015), that forecast averaging at the regional level — in particular based on MSE and rank weights — significantly outperforms the benchmark AR-model (see also Figure 5 in Appendix B) and most of the single indicator-based forecasts (Figure 6 in Appendix B). However, the gain compared to selected indicator models is minor.

5 Conclusion

Based on a newly constructed quarterly series for East German real GDP, we conduct an econometric analysis using quarterly and monthly data in order to nowcast quarterly GDP growth for East Germany. We exactly mimic the real-time information flow faced by the regional economic forecaster within a quarter. Our nowcasting exercise suggests that an ARDL-model including a forecast for total Germany is useful to forecast regional GDP. Furthermore, MIDAS forecasting models containing additional (monthly) information on East Germany significantly improve forecasting quarterly East German GDP growth, although only slightly. MIDAS models encompassing the indicators on situation, expectations and climate in manufacturing and retail trade and vacancies provide a reasonable view about quarterly real GDP growth in East Germany. Moreover, the expectations in construction and capacity utilization in construction turn out to be useful indicators as well. This finding is surprising given the small share of construction (6 %) and trade (12 %) to total gross value added in East Germany. While private construction had the largest share in total Eastern German turnovers in 2017 (almost 42 %), public construction had a share of about 23 % and building construction of 35 %. Therefore, it is worthwhile to scrutinize this sector in more detail. In addition, model averaging yields a significant and consistent picture based on the evaluation of all MIDAS models. Overall, we can confirm that monthly indicators are still useful, and hence, MIDAS models help in improving the nowcast of regional macroeconomic developments in addition to information (forecasts) on national GDP. Finally, the performance of regional GDP forecasts is similar across different information sets within a quarter but differs substantially across quarters.

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Appendix A: The temporal disaggregation approach of quarterly GDP data for East Germany

This appendix describes the estimation of quarterly gross domestic product (GDP) for East Germany (Figure 4). The quarterly series is provided on the web site of the Halle Institute for Economic Research (IWH).[12]

The IWH has regularly provided GDP estimates for East Germany (excluding Berlin) based on quarterly gross value added until 2015 (see *Konjunktur-barometer-Ost*). From 2016 onwards, the calculation is carried out using interpolation methods based on annual regional GDP data as well as quarterly regional indicators.

The most important data sources are the publications of the working group "Regional Accounts" and official employment statistics. Based on gross value added calculations, recent GDP figures are only available at annual frequency and are published with a delay of three months after the end of the reference period.[13] Updates for the first half of a year are published in the summer of the corresponding year. Official quarterly data have not been published since 1999.

Therefore, following the guidelines of the European Statistical System (ESS) (2018), temporal disaggregation, benchmarking and reconciliation methods are used. The use of temporal disaggregation techniques allows the conversion of a lower frequency time series into a higher frequency time series, i.e., from annual to quarterly data. Based on the official annual data for the German regions (East and West), quarterly data are disaggregated using regional quarterly indicators. Deviations from previous publications by the IWH can arise due to the fact that the national accounts of the states are revised up to 5 years into the past.

For the years 1991–1994, corresponding statistics of the Federal Statistical Office (so-called "Schienenhefte") were used as source, in which quarterly figures for the gross domestic product were published for the states.[14] The distribution of current annual values for the gross domestic product is made using the quarterly shares of these former official values. For the period 1995–2015, the IWH uses its own quarterly series, which were determined on the basis of a bottom-up approach (*IWH Konjunkturbarometer*). Starting in 2016, appropriate regional indicators that best reflect the quarterly trend of East German gross domestic product are used to break down the quarters. This approach is described in more detail below.

For temporal disaggregation, it is useful to select a number of appropriate higher-frequency indicators that cover at least the same period as the annual indicator. Indicators should be timely available and not too volatile. In addition, indicators should have a high correlation with the original target variable when converted to the low frequency. Nevertheless, the selection of possible indicators is hampered by the lack of official regional statistics at monthly and / or quarterly frequency and by considerable delay in publication.

In a first step, various eligible indicators were identified. However, the use of all variables in the temporal disaggregation process is not recommended as it may also increase the risk of collinearity. Empirical evidence has shown that the joint use of both output indicators (e.g., turnovers) and input indicators (such as employees) are particularly well suited for disaggregation of GDP in East Germany. Due to high correlation with GDP, monthly data on employees subject to social security contributions and turnover in the manufacturing sector, as well as the quarterly figures for the production index in the manufacturing

[12] `http://www.iwh-halle.de/en/research/data-and-analysis/iwh-macrometer/iwh-indicators-for-east-germany/`

[13] Data on the expenditure side are even published only with a delay of 2–3 years.

[14] Although quarterly data have been published until 1999, these figures cannot be directly used due to revisions of the regional data up to five years.

have been selected. Together, these economic indicators can well reflect the underlying dynamics in East Germany.

Standard temporal disaggregation methods are usually only applicable to one target series and do not consider relationships between multiple time series. However, the use of various indicators may result in an inconsistent picture of the time-disaggregated series, although the annual data are consistent. Therefore, reconciliation methods aim to use a plurality of time series at the same time to disaggregate the target series, without losing consistency. For this approach, the IWH uses the ECOTRIM package provided by EUROSTAT, which includes the multivariate Chow and Lin method (Chow and Lin, 1971) and other temporal disaggregation options for time series.

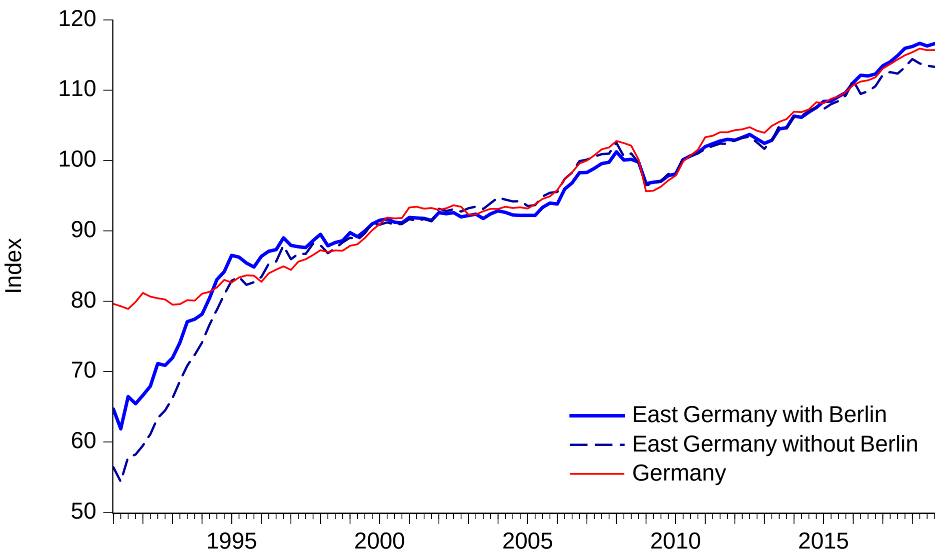
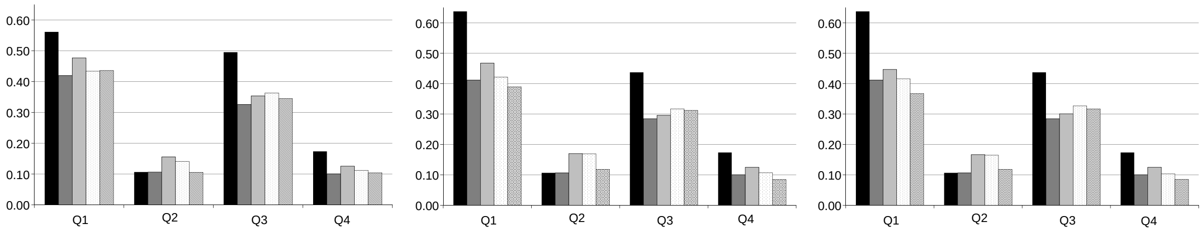


Figure 4: Quarterly East German real GDP and German real GDP

Quarterly gross domestic product, chain-linked volume data, index 2010 = 100, seasonally and calendar-adjusted.
Sources: Federal Statistical Office; working group "Regional Accounts" and own calculations.

By using the X-12-ARIMA procedure, we can finally adjust the data for seasonal and calendar irregularities in Germany. As we perform benchmarking first and then do seasonal adjustment, we end up with small differences in the annual alignment, which are compensated by an annual sum adjustment factor.

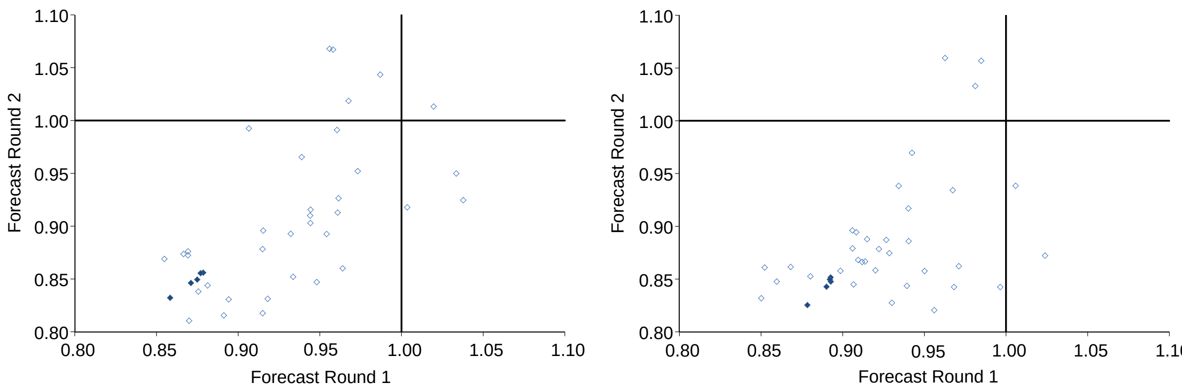
Appendix B: Additional tables and figures



(a) Forecast Round 1 (b) Forecast Round 2 (c) Forecast Round 3

Figure 5: Forecast performance

Mean squared forecast errors are shown for each quarter and different forecast methods. Black – AR model, dark gray – ARDL + IWH forecast, light gray – MIDAS, white and dots – UMIDAS, gray striped – forecast combination. The ARDL-models include the IWH forecast for the current quarter. Forecast combination refers to the forecast averaging models based on MIDAS-models.



(a) MIDAS-Models (b) UMIDAS-Models

Figure 6: Relative forecast errors

Relative root mean squared forecast errors are shown compared to the benchmark AR-model. The forecast performance in forecast round F2 is compared to F1. Results for forecast averaging models are labeled with dark symbols.

Table 4: Indicators used

	availability/ publication lag	frequency	source
GDP			
GDP Germany	1.5 months	quarterly	Federal Statistical Office
GDP East Germany	3 months	biannually	Federal Statistical Office (VGR der Länder)
GDP East Germany, Q1 & Q3	6 months	quarterly	IWH
GDP East Germany, Q2 & Q4	3 months	quarterly	IWH
Hard indicators			
Vacancies (Germany, East Germany)	end of month	monthly	Deutsche Bundesbank
Employees Subject to Social Security (Germany, East Germany)	30 days	monthly	Deutsche Bundesbank
Unemployment Rate (East Germany)	end of month	monthly	Deutsche Bundesbank
Unemployment Rate (Germany)	end of month	monthly	Federal Employment Agency
New Orders in Manufacturing Industry (Germany)	30 days	monthly	Deutsche Bundesbank
New Orders in Manufacturing Industry (East Germany)	on demand	monthly	Federal Statistical Office
Turnover in Manufacturing Industry (Germany)	37 days	monthly	Federal Statistical Office
Turnover in Manufacturing Industry (East Germany)	on demand	monthly	Federal Statistical Office
Turnover in Construction (Germany)	37 days	monthly	Federal Statistical Office
Turnover in Construction (East Germany)	on demand	monthly	Federal Statistical Office
New Orders in Construction (Germany)	37 days	monthly	Federal Statistical Office
New Orders in Construction (East Germany)	on demand	monthly	Federal Statistical Office
Survey indicators			
Manufacturing Industry			
Assessment of the Business Situation	end of month	monthly	ifo Institute
Expect. with respect to Business Developments (t+6)	end of month	monthly	ifo Institute
Business Climate	end of month	monthly	ifo Institute
Construction Industry			
Assessment of the Business Situation	end of month	monthly	ifo Institute
Expect. with respect to Business Developments (t+6)	end of month	monthly	ifo Institute
Business Climate	end of month	monthly	ifo Institute
Capacity utilization	end of month	monthly	ifo Institute
Retail Trade			
Assessment of the Business Situation	end of month	monthly	ifo Institute
Expect. with respect to Business Developments (t+6)	end of month	monthly	ifo Institute
Business Climate	end of month	monthly	ifo Institute
Wholesale Trade			
Assessment of the Business Situation	end of month	monthly	ifo Institute
Expect. with respect to Business Developments (t+6)	end of month	monthly	ifo Institute
Business Climate	end of month	monthly	ifo Institute
Trade and Industry			
Assessment of the Business Situation	end of month	monthly	ifo Institute
Expect. with respect to Business Developments (t+6)	end of month	monthly	ifo Institute
Business Climate	end of month	monthly	ifo Institute

Publication lag for quarterly data refers to previous quarter, for monthly data to previous month, respectively.

Table 5: Forecast properties of quarterly German GDP forecasts

Model	Mean forecast error	Mean absolute forecast error	Mean squared forecast error	variance	unbiased (p-val)	MZ (p-val)	no serial correlation (p-val)
IWH forecast	-0.01	0.28	0.37	0.14	0.83	0.94	0.79
IWH flash forecast	-0.03	0.36	0.44	0.20	0.72	0.33	0.09

Forecast properties of IWH's quarterly GDP forecasts are shown for the period 2011–2018. Tests for unbiasedness and efficiency (Mincer–Zarnowitz) have been conducted.

Table 6: Forecast properties of quarterly benchmark models forecasts

Model	Mean FE	Mean abs. FE	Mean sq. FE	Variance	Bias (p-val)	MZ (p-val)	LB-Q-stat (p-val)
F1							
AR opt	-0.11	0.44	0.55	0.30	0.28	0.21	0.70
ARDL opt	-0.17	0.40	0.51	0.23	0.07	0.19	0.73
mean forecast	-0.14	0.42	0.54	0.27	0.16	0.28	0.85
ARDL opt + IWH forecast DE	-0.07	0.39	0.49	0.23	0.41	0.70	0.83
ARDL opt + IWH flash forecast DE	-0.10	0.43	0.53	0.28	0.28	0.35	0.84
ARDL opt + true GDP	-0.12	0.33	0.44	0.18	0.12	0.27	0.19
F2							
AR opt	-0.12	0.45	0.56	0.30	0.22	0.12	0.87
ARDL opt	-0.15	0.40	0.51	0.23	0.09	0.25	0.70
mean forecast	-0.14	0.42	0.54	0.27	0.15	0.30	0.86
ARDL opt + IWH forecast DE	-0.07	0.37	0.48	0.22	0.40	0.61	0.75
ARDL opt + IWH flash forecast DE	-0.10	0.41	0.52	0.26	0.28	0.44	0.79
ARDL opt + true GDP	-0.11	0.45	0.56	0.31	0.27	0.10	0.50

Forecast performance of benchmark models for East German GDP growth for the period 2011–2018. Tests for unbiasedness, efficiency (Mincer–Zarnowiz) and autocorrelation (Ljung–Box Q-statistics) have been conducted for the forecast errors (FE).

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ISSN 2194-2188

Leibniz
Association