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Nowcasting German GDP: Foreign factors, financial markets, and model averaging

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ABSTRACT

This paper develops a nowcasting model for the German economy. The model outperforms a number of alternatives and produces forecasts not only for GDP but also for other key variables. We show that the inclusion of a foreign factor improves the model's performance, while financial variables do not. Additionally, a comprehensive model averaging exercise reveals that factor extraction in a single model delivers slightly better results than averaging across models. Finally, we estimate a "news" index for the German economy in order to assess the overall performance of the model beyond forecast errors in GDP. The index is constructed as a weighted average of the nowcast errors related to each variable included in the model.

Nowcasting models are routinely used in policy institutions and the private sector. They are designed to forecast the present, the recent past, and the near future. The aim of these models is to obtain timely updates of estimates of the current state of the economy by exploiting information from newly released data. Since national accounts are recorded quarterly, are published late (often more than one month after the close of the quarter), and are subsequently revised, a sequence of nowcast updates can provide a progressively more accurate view of "where we are now".

The paper by Giannone et al. (2008) was the first to formalize the nowcasting problem in a comprehensive framework. That framework allows for the use of a large number of data series, possibly available at different frequencies and with different publication lags. We build on that contribution and develop a state-of-the-art, mixed-frequency nowcasting model for the German economy.

The existing literature has applied several methodological approaches to nowcasting GDP. For example, Antolin-Diaz et al. (2021) and Cimadomo et al. (2020) apply Bayesian methods to forecast US economic output. To predict German GDP, Carstensen et al. (2009) and Pinkwart (2018) use bridge equations, and Strohsal and Wolf (2020) employ filtering techniques. Our paper

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is closely related to Marcellino and Schumacher (2010), who apply a MIDAS approach to German data. Unlike them, we use a factor model approach, as in Stock and Watson (2002a, 2002b), Forni et al. (2000), and Bańbura et al. (2013). As the literature suggests, factor models have desirable properties when there is strong comovement between the data, as is often the case with economic time series. Factor models also provide forecasts for all variables included in the model and allow changes in the forecast of one variable to be attributed to a data release or revision of another variable. Factor models can also be easily cast into a state-space representation, which allows us to update the factor estimate via the Kalman filter while using an expectation–maximization algorithm to deal with mixed-frequency data. The asymptotic properties of such a model under some general conditions have been analyzed by Doz et al. (2012) and more recently by Barigozzi and Luciani (2020). An expectation–maximization algorithm for a general pattern of missing data was designed by Bańbura and Modugno (2014). The model (or some versions of it) has been successfully applied to many countries in published work and in policy work.[2]

We apply our nowcasting model for Germany to a number of alternative data sets. Specifically, we study the effect of including financial variables and foreign indicators on the accuracy of the model. The results indicate that foreign variables prove helpful for nowcasting, while financial variables do not. The most accurate model includes 24 real, domestic German variables and an exogenous foreign factor which we estimate from a separate euro area model. Introducing a single foreign factor is a parsimonious way to allow foreign economic development to affect the nowcasts of the GDP of Germany, a highly open economy.

Confirming a common result from the literature, we show that the progressive arrival of data improves the forecast error of GDP throughout the quarter. This supports the intuition that exploiting timely data releases provides an informational advantage, even if the significance of timely data typically vanishes as soon as less timely but more reliable hard information is released. In other words, the marginal significance of a data release depends on the information set available at the time.

We also conduct an extensive model averaging exercise. We find that factor extraction in a single model delivers slightly better results than averaging across different models. Finally, we show how to construct an index of the model's surprises ("news"). This index provides a comprehensive view on the direction of overall errors (see Caruso (2019) for an analysis of US data).

The next section presents the data. The methodology is explained in Section 3. Section 4 documents the empirical performance of the model and studies the role of foreign and financial variables. The model averaging exercise is shown in Section 5 and the "news index" in Section 6. The last section concludes.

2. Data, data characteristics, and the calendar

We consider 50 real, nominal and financial series over a sample from January 1991 to September 2018. The variables are shown in Table 1, which shows, for each of them, the transformation, frequency, and average publication lag. The transformation of the variables is chosen to achieve stationarity. The publication lag is measured as the number of days from the end of the reference period to the release date. A positive number implies that the variable is released after the reference period, and vice versa. Most series are calendar- and seasonally adjusted.[3]

Table 1 also shows the seven alternative data sets that we use to estimate the model. We choose these seven models since they allow us to separately evaluate the impact of auxiliary foreign factors, euro area variables, and nominal and financial variables on the forecasting performance. We now comment on each of those categories one by one.

The upper panel of Table 1 shows the 24 real variables that are included in each of the seven models. This set of variables also includes a number of surveys, for example the ifo Business Climate Index and the German Purchasing Managers' Index (PMI). We include these surveys, since they have a short publication lag and should therefore be particularly useful at the beginning of the quarter when no other data relating directly to the current quarter are available. Additionally, we use hard data on German economic activity, for example industrial production and new orders. These series are published with a longer lag. Hence, they should be particularly useful during later periods in the reference quarter. In addition to GDP, we consider four other quarterly series from the national accounts.

The second panel of Table 1 shows two foreign factors, one for the euro area and one for the US. For an export-oriented economy like Germany, economic developments in other countries are likely to have an impact on domestic GDP. These factors are taken from two separate models, one for the euro area and one for the US; see Appendix.[4] Introducing auxiliary factors is a parsimonious way to take into account the effect of foreign economic developments on the German economy.[5] The factors are computed in real time, so that every time a variable included in either the euro area or US model is released, the relevant foreign factor is revised, leading to revisions of the nowcast for all the German variables included in the model. We use US and euro area factors since both

2 See Cascaldi-Garcia et al. (2021) for a recent application to euro area data.

3 The exceptions are new passenger car registrations, passenger car production, and total housing permits, which are transformed to yearly growth rates. ZEW economic sentiment is also not seasonally adjusted and is transformed to yearly differences.

4 The two factors are estimated via two dynamic factor models applied separately to euro area and US data. The euro area model is the same as that in Bańbura and Modugno (2014), and the US model is the same as that in Giannone et al. (2008).

5 Our model is more parsimonious than a model that includes a euro area factor directly, because euro area variables do not have their own equations and hence there are fewer parameters to be estimated. Our model can be thought of as a factor model where the euro area factor enters as a variable, rather than as an additional factor.

Table 1
Data set: German variables, euro area (EA) economic activity, and financial market data.

N	Descriptions	Tcd	Freq	Lag	Models						
					I	II	III	IV	V	VI	VII
1	ZEW Economic Sentiment	6	M	−34	x	x	x	x	x	x	x
2	ifo Business Climate Index: All sectors	1	M	−6	x	x	x	x	x	x	x
3	ifo Business Situation: Industry & Trade	1	M	−6	x	x	x	x	x	x	x
4	PMI: Manufacturing - Flash	1	M	−5	x	x	x	x	x	x	x
5	PMI: Services Business Activity - Flash	1	M	−4	x	x	x	x	x	x	x
6	Consumer Climate Index	1	M	−3	x	x	x	x	x	x	x
7	BA-X Job Index	4	M	0	x	x	x	x	x	x	x
8	Total Domestic Employment	2	M	1	x	x	x	x	x	x	x
9	Passenger Car Production	4	M	2	x	x	x	x	x	x	x
10	Job Vacancies	3	M	1	x	x	x	x	x	x	x
11	New Passenger Car Registration	4	M	3	x	x	x	x	x	x	x
12	Retail Sales Index excl Autos	3	M	32	x	x	x	x	x	x	x
13	New Orders: Manufacturing	3	M	37	x	x	x	x	x	x	x
14	Total Sales: Manufacturing	3	M	37	x	x	x	x	x	x	x
15	Ind Production excl Construction	3	M	38	x	x	x	x	x	x	x
16	Ind Production: Construction	3	M	38	x	x	x	x	x	x	x
17	Exports	3	M	39	x	x	x	x	x	x	x
18	Imports	3	M	39	x	x	x	x	x	x	x
19	Total Housing Permits	4	M	50	x	x	x	x	x	x	x
20	GDP	5	Q	43	x	x	x	x	x	x	x
21	GDP: Private Consumption	5	Q	54	x	x	x	x	x	x	x
22	GDP: Government Consumption	5	Q	54	x	x	x	x	x	x	x
23	GDP: Investment: Construction	5	Q	54	x	x	x	x	x	x	x
24	GDP: Investment: Equipment	5	Q	54	x	x	x	x	x	x	x
25	EA factor	1	M	NA		x	x			x	
26	US factor	1	M	NA			x				
27	EA 18: Ind Production excl Construction	3	M	38				x			x
28	EA 18: Manufact New Orders	3	M	38				x			x
29	EA 18: Manufact Turnover	3	M	38				x			x
30	EA 18: Ind Production Construction	3	M	38				x			x
31	EA 18: Retail Sales	3	M	36				x			x
32	EA 18: Import	3	M	39				x			x
33	EA 18: Exports	3	M	39				x			x
34	EU 27: New Passengers Car Reg	4	M	3				x			x
35	EA: PMI Manufact	1	M	−5				x			x
36	EA: PMI Business Activity	1	M	−5				x			x
37	EA 18: Business Climate Index	1	M	−4				x			x
38	EA 18: Consumer Confidence Ind	2	M	−3				x			x
39	Money Supply: M2	3	M	22					x	x	x
40	Harmonized Index of Consumer Prices	3	M	22					x	x	x
41	Harmonized PPI: Industry excl Construction	3	M	22					x	x	x
42	Negotiated Hourly Earnings	3	M	50					x	x	x
43	Negotiated Monthly Earnings	3	M	50					x	x	x
44	WTI Oil Price	3	M	0					x	x	x
45	Yield on All Outstanding Debt	3	M	0					x	x	x
46	Base Rate EOP	3	M	0					x	x	x
47	Exchange Rate EUR–USD	3	M	0					x	x	x
48	Stock Market Index: DAX	3	M	0					x	x	x
49	S&P 500 Price	3	M	0					x	x	x
50	GDP Deflator	3	Q	43					x	x	x

Notes: Transformation code ("Tcd"): 1, the series is in levels; 2, the series is in first differences; 3, the series is in monthly log-differences; 4, the series is in yearly log-differences; 5, the series is in quarterly log-differences; 6, the series is in yearly differences. The sample period is from January 1991 to September 2018. The publication lag is measured as the average number of days between the end of the reference period and the publication date. Models I to VII include the variables which are checked by an "x".

of these economies are important trading partners for Germany and there are high-quality monthly data series available for both economies. In addition to the trade link, the euro area, the US, and Germany are connected via their financial systems. China, certainly another important trading partner for Germany, does not make the same type of high-quality data available.

The third panel of Table 1 contains 12 real variables related to the euro area. Directly introducing foreign variables into the model is an alternative method to including auxiliary factors for foreign activity. It also allows us to compare the performance of the model with foreign factors to the one that directly introduces foreign variables. The euro area variables include a number of surveys and timely indicators, such as euro area PMIs, business climate indexes, and consumer confidence indexes, as well as data on actual realizations such as industrial production.

The lower panel of Table 1 shows 12 series: seven nominal variables and five financial variables. Nominal price variables, such as the HICP and the PPI, are released ahead of most hard data, while nominal earnings variables are among the last variables to be released. WTI oil price is released at a higher frequency than the monthly frequency of the nowcasting model, but we include it in the model as a monthly average and assign the last day of each month as the release date. All the financial variables are very timely because they are available daily. To incorporate them in the monthly model, we use end of period values.

Variable selection was based on two informal criteria. First, we included series that improved the historical forecasting performance of the model. Second, even if series only marginally improved the performance of the model, we included them if they are of high interest for market participants and policymakers (e.g. retail sales). We did not include disaggregated data series into the model. The main reason for that is that, as shown in Bańbura et al. (2011), including disaggregate series into a factor model usually neither helps nor harms the forecasting performance of the model. We obtained the same result for Germany. The one exception we make is for disaggregated national accounts data, such as consumption expenditure and investment, which we include because their own forecasts are of economic interest.

3. Nowcasting model

The general description of the nowcasting problem and the empirical approach closely follows Bańbura et al. (2011). Let us denote $y_t^m = (y_{1,t}^m, y_{2,t}^m, \dots, y_{N_m,t}^m)'$ as the vector of standardized and stationarized monthly variables at time t. Further, let us denote $Y_t^q = (Y_{1,t}^q, Y_{2,t}^q, \dots, Y_{N_q,t}^q)'$ as a vector of log-transformed quarterly variables. Here, N_m is the number of monthly variables, and N_q is the number of quarterly variables. We collect monthly and quarterly data in the vector $y_t = (y_t^m, y_t^q)'$.

We assume that each variable in y_t is driven by few common factors capturing the most correlated components of the panel and a variable-specific (idiosyncratic) component. This model allows us to exploit in a parsimonious way the effect of correlated data on the output variables and has been studied for large panels of time series by Giannone et al. (2008) and Doz et al. (2011).

We have:

$$y_t = \Lambda F_t + \varepsilon_t, \tag{1}$$

where F_t is an $r \times 1$ vector of unobserved common factors with r being the number of common factors, $0 < r < N_m + N_q$, ε_t is the vector of idiosyncratic components, and Λ is the matrix that contains the factor loadings. The factors are modeled as a VAR process of order p. Formally,

$$F_t = C_1 F_{t-1} + \cdots + C_p F_{t-p} + u_t \qquad u_t \sim i.i.d.\ N(0, Q), \tag{2}$$

where $C_1, \dots, C_p$ are the $r \times r$ matrices that contain the autoregressive coefficients. We allow for serial correlation in the errors and model the idiosyncratic components as an AR(1), such that

$$\varepsilon_{i,t} = \rho_i \varepsilon_{it-1} + e_{i,t} \qquad e_{i,t} \sim i.i.d.\ N(0, \sigma_i^2), \tag{3}$$

with $\mathbb{E}[e_{i,t} e_{l,t}] = 0$ for $i \neq l$.

To design a model for nowcasting, we need to have a strategy for considering mixed-frequency data (in our case monthly and quarterly) and missing observations at the end of the sample. Indeed, data releases are not synchronized. At each point of time, for example, we may have information on the current month for some variables but only up to the last month for others. This leads to a panel with a "jagged" edge.

Let us mention that the mixed-frequency problem is handled as in Mariano and Murasawa (2003), who consider the quarterly variable, $Y_{i,t}^q$, as a partially observed monthly variable. As for missing observations, we write the model in its state-space form and estimate the parameters by maximum likelihood. Given the estimated parameters, we use the Kalman filter to update the estimate of the factors and the nowcasts as new data are released.

Let us stress that the nowcast of each variable in the panel is updated whenever new data are released. The update is a function of the nowcast errors (the model's surprise or news) and the impact on each variable that the model assigns to that error. A more formal explanation is as follows.

Let $t = 1, \dots, T$ and $\nu = 1, \dots, V$ indicate the reference periods and data vintages at our disposal. Further, define the nowcast of the ith variable as $\mathbb{E}[y_{i,t}|\Omega_\nu]$, the expectation of the $y_{i,t}$ conditional on the information set Ω_ν at time ν. At time $\nu + 1$, we observe the release of variables $\{y_{j,T_{j,\nu+1}}, j \in J_{\nu+1}\}$, where $T_{j,\nu+1}$ is the reference month of a given released variable y_j. Following the release, the information set expands to $\Omega_{\nu+1} \subset \Omega_\nu$ and the nowcast is revised according to

$$\mathbb{E}[y_{i,t}|\Omega_{\nu+1}] = \mathbb{E}[y_{i,t}|\Omega_\nu] + \mathbb{E}[y_{i,t}|I_{\nu+1}] \tag{4}$$

where $I_{\nu+1}$ is the information in $\Omega_{\nu+1}$ that is orthogonal to Ω_ν. We can decompose the change in the nowcast of $y_{i,t}$ due to the new information as the weighted sum of the *news* associated to each variable release. That is,

$$\mathbb{E}[y_{i,t}|I_{\nu+1}] = \sum_{j \in J_{\nu+1}} b_{j,t,\nu+1}(y_{j,T_{j,\nu+1}} - \mathbb{E}[y_{j,T_{j,\nu+1}}|\Omega_\nu]) \tag{5}$$

where $b_{j,t,\nu+1}$ is the weight corresponding to the release of variable j. In the remainder of the paper, $\mathbb{E}[y_{i,t}|I_{\nu+1}]$ is referred to as the *impact* and $y_{j,T_{j,\nu+1}} - \mathbb{E}[y_{j,T_{j,\nu+1}}|\Omega_\nu]$ as the *news*.

Given an estimate of the parameters, the nowcasts, the *news*, and the corresponding weights can be obtained via a run of the Kalman filter and smoother.

4. Empirical analysis of the different models

We consider seven different models (refer to Table 1 for the specification of variables):

1. *Model I*. Domestic German real variables only, including surveys. This is our baseline model.
2. *Model II*. Model I augmented by a factor obtained by the estimation of a euro area model (see Appendix).
3. *Model III*. Model II augmented by a factor obtained by the estimation of a US model (see Appendix).

Table 2
Comparison of RMSEs relative to the AR(1) benchmark.

Model	Forecasting		Nowcasting			Backcasting
	32 weeks	26 weeks	20 weeks	14 weeks	8 weeks	2 weeks
Model I	0.96	0.91	0.75	0.69	0.47	0.39
Model II	**0.92**	**0.81**	**0.68**	**0.63**	0.51	0.47
Model III	0.96	0.82	0.69	0.64	0.57	0.54
Model IV	0.95	0.86	0.70	0.66	**0.44**	**0.38**
Model V	0.98	0.93	0.75	0.70	0.53	0.47
Model VI	0.95	0.82	0.69	0.64	0.55	0.51
Model VII	0.99	0.90	0.68	0.63	0.52	0.49
Bridge equation model	1.00	0.87	0.75	0.70	0.60	0.53

Notes: This table reports the RMSE of the baseline dynamic factor model (DFM), the DFM augmented by a euro area factor, by a euro area and US factor, by euro area variables, by nominal variables, by a euro area factor and nominal variables, and by euro area and nominal variables, relative to the RMSE of an AR(1). Additionally we include the results from the bridge equation model of Pinkwart (2018). Relative RMSEs are reported for different dates relative to the release date of German GDP. For example, the RMSEs at 32 weeks refer to the RMSEs 32 weeks prior to the release date. The variables included in Models I to VII are described in Table 1.

4. *Model IV*. Model I augmented by euro area variables (this model differs from Model II insofar as euro area information is included using individual time series rather than an aggregate factor).
5. *Model V*. Model I augmented by nominal and financial variables.
6. *Model VI*. Model II augmented by nominal and financial variables.
7. *Model VII*. Model IV augmented by nominal and financial variables.

For all models, we set the number of factors and the lag order of the VAR process for the factors equal to two. The choice of the number of factors is informal and based on the principal component analysis reported in Table 4 in the Appendix, which suggests only marginal contributions from additional principal components. We report the results from different specifications in Section 5.

For the out-of-sample evaluation, we compute nowcasts from January 2006 until September 2018. The analysis is performed in pseudo-real time. This implies following the historical pattern of data releases, but only using the latest available vintage of data. The estimation is done recursively using an expanding window scheme.

Table 2 reports the out-of-sample root mean square forecast errors (RMSE) for all models. All RMSEs are calculated relative to a naive forecast based on an autoregressive process of order 1. We also compare our model to forecasts generated by a recent bridge equation model implemented at the Deutsche Bundesbank (see Pinkwart, 2018). The bridge equation model follows a bottom-up approach which closely mirrors the construction of national accounts by the German Federal Statistical Office. Its main advantage is that it forecasts all components from both the production side and the expenditure side of GDP. The results are then aggregated using the weighting scheme of the statistical office.

In bold, we identify the best performing model for each forecast horizon. Several results stand out. All models produce more precise nowcasts as we get closer to the GDP release, since more information becomes available over time. Notice also that all models outperform the AR(1). Compared to Model I and the bridge equation model, models that include euro area variables or euro area factors (II and IV) perform better. Only in the backcasting period does Model II have a slightly higher RMSE than Model I. Importantly, nominal and financial variables and the US factor do not seem to add forecasting power. While the limited forecasting power of financial variables for GDP is a common finding, the result for the US factor is somewhat counter-intuitive. Our interpretation is that the US factor does not add forecasting power beyond the euro area factor because the model behind the euro area factor already picks up economic developments in the US through a large number of surveys.

The analysis suggests that euro area variables matter (Model II and Model IV) for nowcasting German GDP, and that the difference between including them as euro area factors or as individual euro area variables is small. We prefer Model II, since it produces more accurate forecasts until eight weeks before the release of GDP.

In general, all forecasts based on the factor models are highly correlated, as illustrated in Fig. 1, which plots the pseudo-real-time nowcast for all models against revised GDP quarterly growth.

4.1. Performance over time: What is the role of euro area information?

In this section we evaluate in greater detail the role of euro area information for the nowcast of the German economy. To this end, we focus on Model II and Model I and study their respective performance for the GDP nowcast over time.

To assess the value of incoming information, we follow Giannone et al. (2008) and compute the average RMSE over the forecasting period. The top panel in Fig. 2 shows the average RMSE from the beginning to the close of the quarter computed over the whole sample period. To demonstrate the effect of the euro area factor on the forecasting performance, we plot the RMSE for Model I and Model II against an AR(1) benchmark. The forecast error of the two models decreases over time as more information becomes available, confirming the results obtained in the literature for several countries (Angelini et al., 2011, D'Agostino et al., 2013, Anesti et al., 2021, Bragoli, 2017, Bragoli et al., 2015, Bragoli & Fosten, 2018, and Caruso, 2018). The euro area factor included in Model II helps at the forecast and nowcast horizon and only

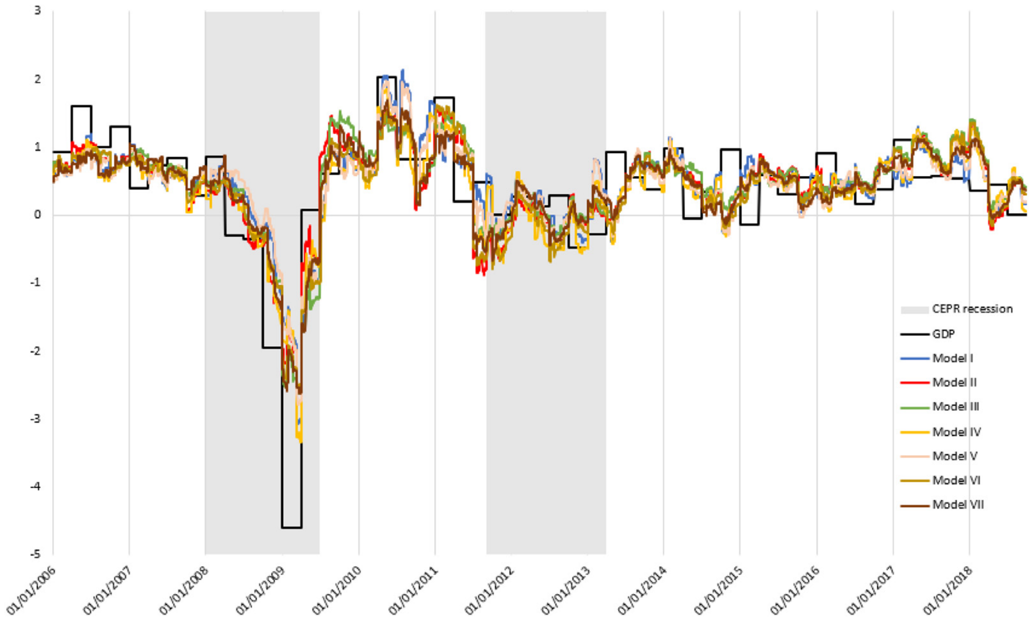


Fig. 1. Realized GDP versus nowcast reconstruction. *Notes*: This figure shows the nowcast reconstruction in pseudo-real time of all the models, computed using the dynamic factor model. The black line is GDP out-turn, the blue line is Model I, the red line is Model II, the green line is Model III, the yellow line is Model IV, the pink line is Model V, the light brown line is Model VI, and the dark brown line is Model VII. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

slightly worsens the results at the backcast horizon. The parsimonious way of incorporating euro area information through a single factor instead of 12 variables (cf. Table 1) thus pays off.

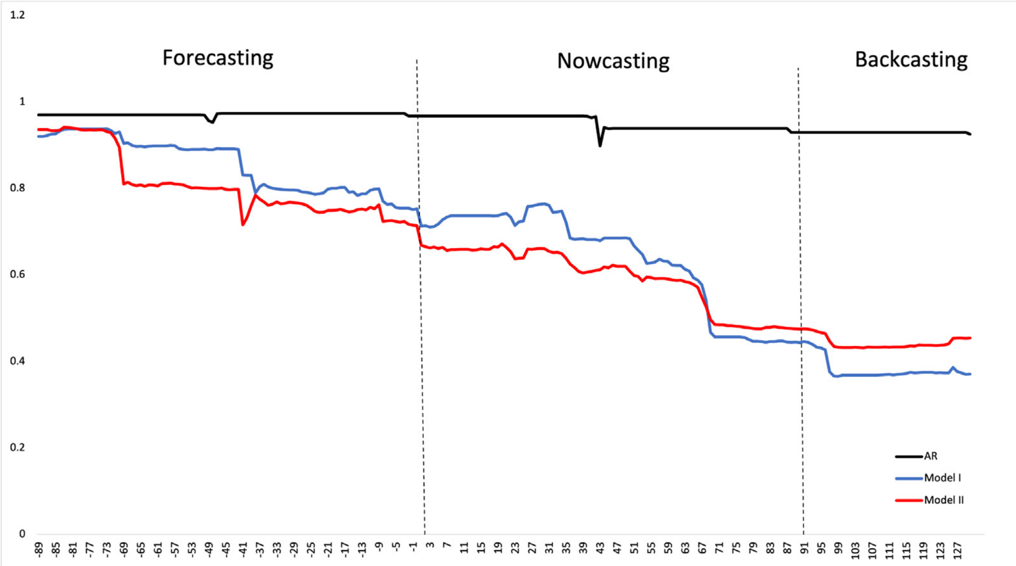
The bottom panel in Fig. 2 shows the average RMSE for the same two models but computed over a sample excluding the CEPR recession dates. On the restricted sample, Model I, which does not include euro area variables, slightly outperforms Model II, which includes the euro area factor. This implies that the superior performance of Model II on the whole sample is driven by greater forecasting accuracy during downturns. Euro area information is especially useful during recessions but does not improve the forecasting performance during normal times.

Fig. 3 shows the nowcast reconstruction in pseudo-real time for Model I and Model II against quarterly GDP.[6] It further illustrates that recessions matter. Model II outperforms Model I in the downturn and recovery of 2008–2009, reflecting the global nature of the crisis. However, it does slightly worse in 2011 when Germany did not follow the rest of the euro area in the debt-related recession.

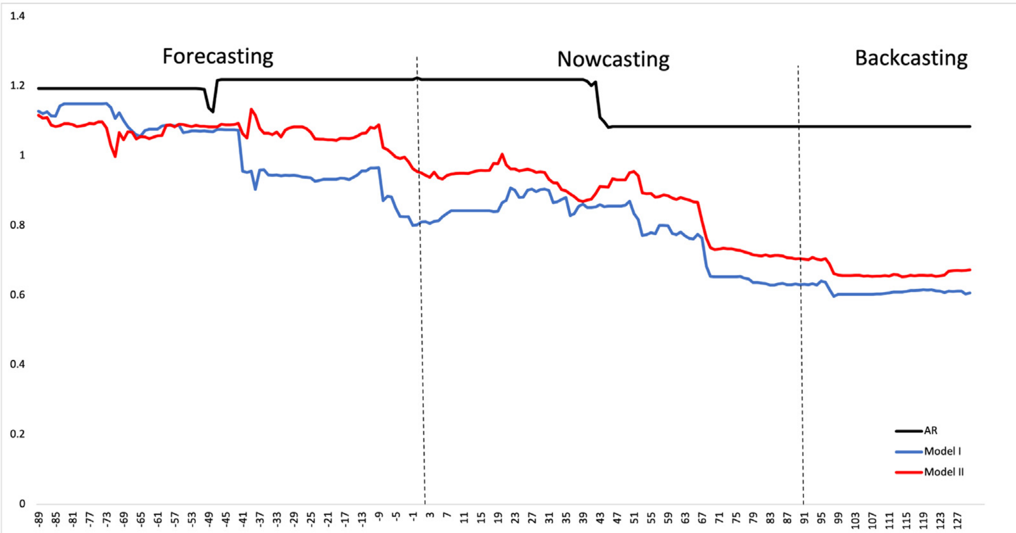
We now study the impact of individual variables on the nowcast for Model II. For that purpose, we follow a great number of nowcasting papers, including Bragoli and Modugno (2017) and Caruso (2018), and compute the average impact of each variable on predicted GDP during the nowcasting period, which we plot in Fig. 4. The impact is defined as the product of the "news", i.e. the difference between the model's prediction and the actual release of a particular variable, and the associated weight in the GDP estimate; see Eq. (5). In line with the results in Giannone et al. (2008), for most survey data, the impact is largest in the first month of the reference quarter and then declines. The euro area factor has a moderate average impact and, similar to the surveys, it displays a decline in impact from the first to the last month of the quarter. Hard data are most influential in the third month when the released series, with a publication lag of around 40 days, are actually referring to the first month of the reference quarter. In the second month, the release of GDP, referring to the previous quarter, has a substantial impact on the nowcast. Other disaggregated quarterly figures from the national accounts—for instance, investment or private consumption expenditures—do not add much to the information content of aggregate GDP. This may be due to their release date, which is about 10 days after that of GDP.

To further illustrate the effects of data releases on forecast revisions, we follow Bańbura and Modugno (2014) and study the effect of data releases for specific quarters. Fig. 5 shows a replicated real-time nowcast of GDP for the third quarter of 2008. The top panel shows the nowcast from Model I and the bottom panel shows the nowcast from Model II. The period starts with the forecast in April 2008, continues over the nowcast period from July to September, and ends with the official release of GDP on November 14th. The value shown for the official release

[6] The nowcast reconstruction is created recursively, using parameters from an initial estimation sample to generate out-of-sample nowcasts for a year after the end of the estimation sample, then re-estimating the parameters with out-turn data from that year to generate the next year's series of nowcasts, and repeating this process up to the end of the out-of-sample reconstruction. This exercise is done using an accurate historical calendar of release dates for the series used in the model, but using only revised values for those releases, because revision histories are not available. We call this a "pseudo-real-time" reconstruction.



(a) RMSE on the whole sample.



(b) RMSE on the sample excluding CEPR recessions.

Fig. 2. Both panels in this figure show the RMSE evolution along the forecast horizon for Models I and II versus an AR(1) benchmark. The black line is the AR(1), the blue line is Model I, and the red line is Model II. Panel (a) shows the RMSE computed on the whole sample. Panel (b) shows the RMSE computed over the sample excluding CEPR recessions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

is the latest revised value, although the date on which it is shown on the graph is the date of the first release. For the purpose of exposition, we group the variables into a few broad categories.

For Model II, the first strong downward revision of the GDP prediction comes with the release of euro area data captured by the auxiliary factor. In fact, during the whole forecasting period, the euro area factor dominates the forecast revisions for Model II. This emphasizes the role of euro area economic development as a leading indicator for German GDP during the financial crisis. Apart from that, only minor impacts result from survey data. Thereafter, from August onwards, the news impact from the other variables becomes more sizable, although the nowcast remains relatively stable. Later in the reference quarter, hard data (e.g. manufacturing and housing data) become more important. Yet, in the particular case of the third quarter of 2008, the hard data released in October gave an overly optimistic signal and pushed the nowcast in the wrong direction.

Model I does not include the euro area factor, and therefore detects the downturn only when manufacturing data begin to be realized, which is much later than Model II. Model I never recognizes the severity of the downturn

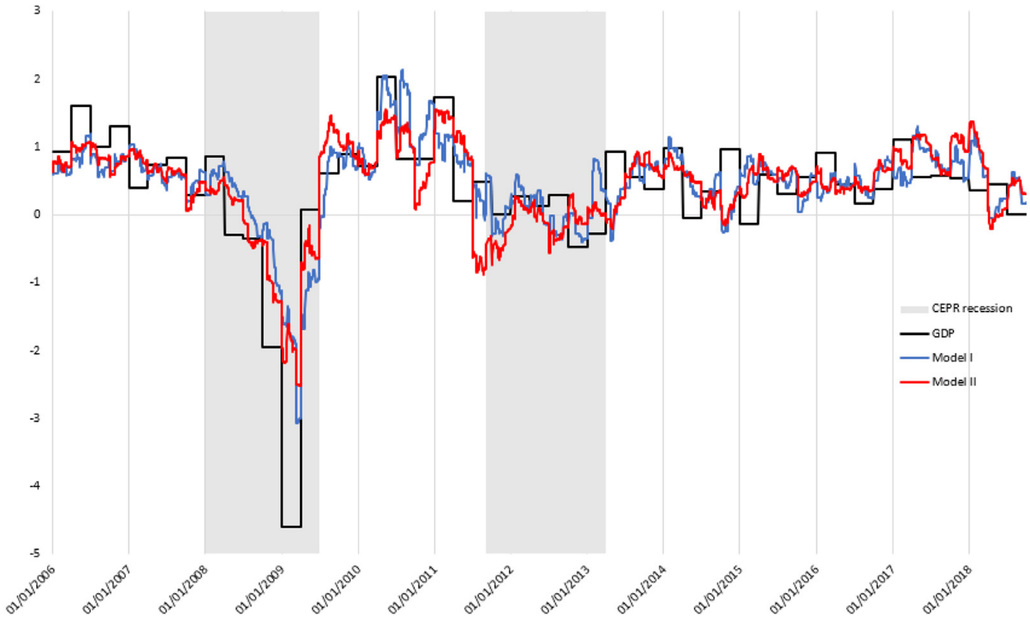


Fig. 3. Realized GDP versus German dynamic factor model. *Notes*: This figure shows the nowcast reconstruction in pseudo-real time of Model I versus Model II. The black line is the GDP, the blue line is Model I, and the red line is Model II. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

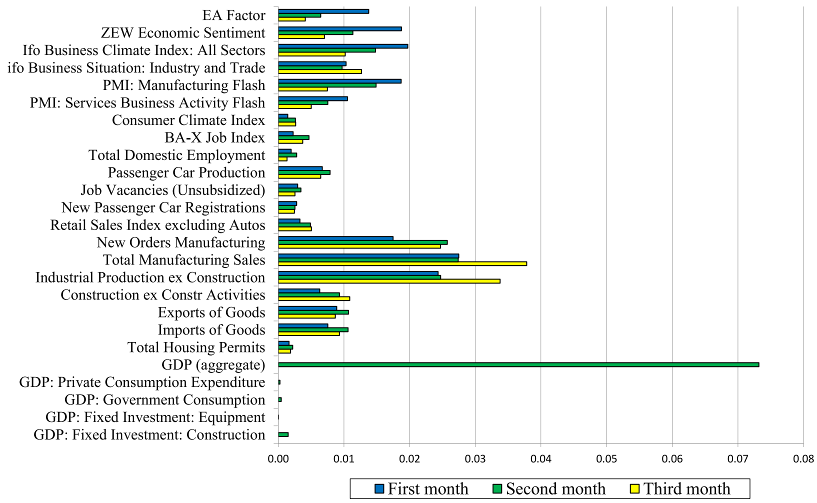


Fig. 4. Impact of individual series on predicted GDP.

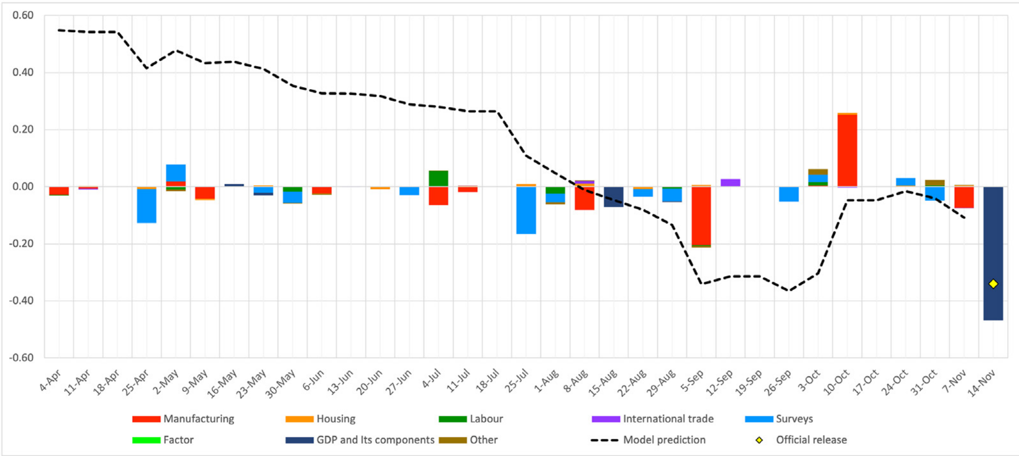
and, on the day of the GDP release, ends up with a much larger forecast error than Model II.[7]

4.2. Nowcasting and financial variables

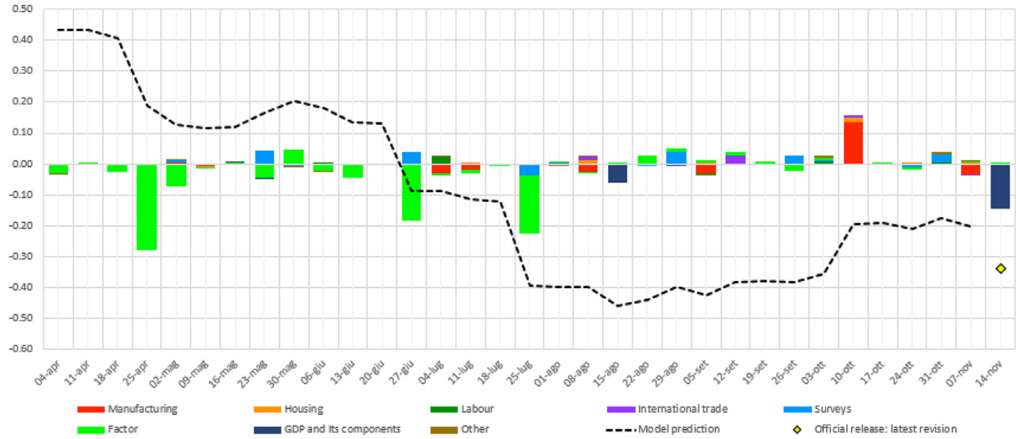
As described in Section 4, the model that contains nominal and financial variables does worse than the model with real variables only, a result that is consistent with earlier findings in the literature; see, for example, Forni et al. (2003). Here, we provide some descriptive statistics to shed light on that finding in the case of Germany.

Fig. 6 plots the first estimated factor of Model II, which loads mostly domestic real variables, against the DAX index, both monthly but transformed in quarter-on-quarter growth rates in order to smooth high-frequency volatility. The correlation between the first factor and the DAX is 21%, and the two variables seem to be coincident. Heuristically, the picture suggests that financial markets reflect the information in the macroeconomy, as summarized by the first factor, contemporaneously, but that there are no leading indications in financial markets.

7 Charts that show additional event studies for different quarters are available in Appendix.



(a)



(b)

Fig. 5. (a) Contribution of news to forecast revisions for 2008Q3 in Model I (i.e. the model without the euro area factor). (b) Contribution of news to forecast revisions for 2008Q3 in Model II (i.e. the model with the euro area factor).

5. Model averaging exercise

Up to now, we have reported results for a particular parametrization of the model (two factors, $r = 2$, and two lags, $p = 2$). In order to investigate the robustness of our results, we perform a model averaging exercise that consists of taking the seven models described above and computing the average of their performance across different specifications, as in Timmermann (2006) and Rapach et al. (2010).

For each of the seven models, we compute the nowcast for all four combinations of $r = 1, 2$ and $p = 1, 2$ and then compute the average of these four versions for each model. Finally we compute the average of all 28 specifications. The results are reported in Table 3. For Models I–VII in the first seven rows of the table, we show the RMSE of the model average relative to the RMSE of the model with the standard specification of $r = 2$ and $p = 2$. The second-to-last row of the table ("Average all") shows the RMSE of the average across all the models and all possible specifications relative to the RMSE of Model II, the most accurate model. The last row ("Average $r = 2$, $p = 2$") shows the average of all seven models using the standard parametrization relative to the RMSE of Model II. A number greater than 1 indicates that the model with standard specification performs better than the model average.

Two results emerge from this analysis. First, averaging across different specifications and models does not improve the performance of the best model with fixed $p = 2$ and $r = 2$. Indeed the average for Model II, the most accurate model, performs worse than Model II, as indicated by relative RMSEs greater than 1. Second, the average of the averages does not improve over the average of the different specifications of Model II.

The finding that averaging does not increase the nowcast precision may seem counter-intuitive, and it is in contrast to common results from the forecasting literature. One explanation is the fact that, as seen in Table 2, all models have a relatively similar nowcasting performance. Notice that the best factor model performs slightly better than an average across models. This suggests that

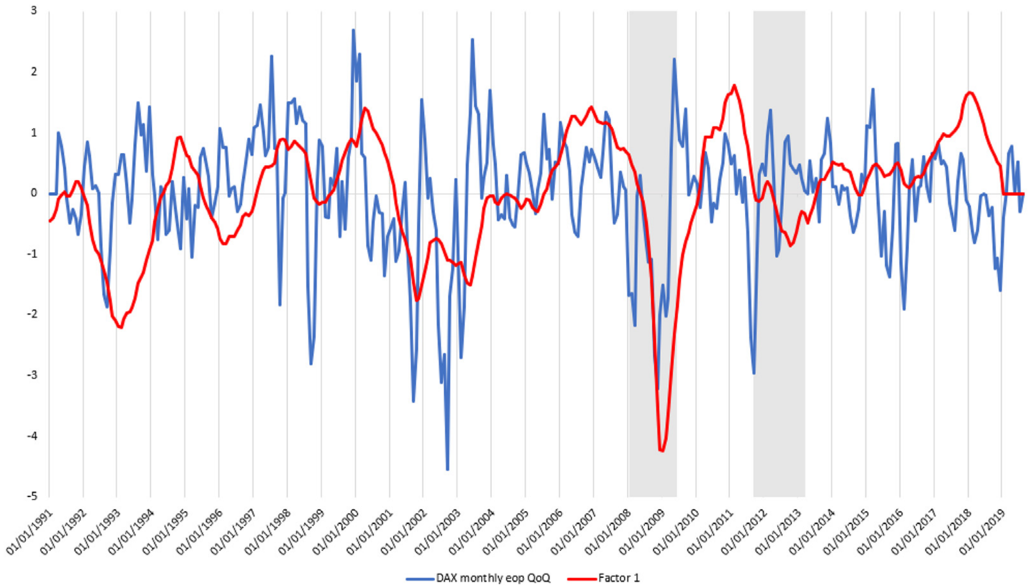


Fig. 6. DAX versus the first factor of Model II.

Table 3
Model average RMSE against the AR(1) benchmark.

Model	Forecasting		Nowcasting			Backcasting
	32 weeks	26 weeks	20 weeks	14 weeks	8 weeks	2 weeks
Model I	1.01	1.01	1.07	1.12	1.55	1.81
Model II	1.01	1.02	1.06	1.10	1.31	1.40
Model III	1.02	1.04	1.07	1.11	1.23	1.28
Model IV	1.06	1.08	1.06	1.06	1.41	1.58
Model V	0.99	1.00	1.08	1.13	1.42	1.57
Model VI	0.99	1.05	1.12	1.17	1.33	1.41
Model VII	1.03	1.04	1.10	1.11	1.19	1.22
Average all	1.04	1.11	1.12	1.16	1.33	1.40
Average $r = 2$, $p = 2$	1.02	1.05	1.03	1.03	1.02	1.00

Notes: This table reports the average RMSE for each of the seven models, the average being calculated from four different parametrizations in each case. For Models I–VII in the first seven rows of the table, the RMSE is shown relative to the RMSE of the respective model. Additionally, we include the RMSE of the average across all the models and all the possible specifications ("Average all") relative to the RMSE of Model II. Lastly, we show the average of all seven models using the standard parametrization ("Average $r = 2$, $p = 2$") relative to the RMSE of Model II. Relative RMSEs are reported for different dates relative to the release date of German GDP. For example, the RMSEs at 32 weeks refer to the RMSEs 32 weeks prior to the release date.

averaging across variables via factor extraction is more efficient than averaging across models. Another possible interpretation is misspecification. Using fewer factors and lags does not provide additional forecasting power when combined in an average forecast. This is also in support of our baseline specification, where we use $r = 2$ and $p = 2$.

6. Overall performance and the "news index"

Since our model produces predictions for all variables included, it is economically interesting to report some results for variables other than GDP. For example, let us examine the model's prediction of the ifo Business Climate Index, which is a timely survey closely watched by financial markets, governments, and many other institutions. Fig. 7 reports the index and the model's prediction the day before the official release. The figure shows that the model tracks the index quite well. Indeed, the model has an RMSE, measured on the day before the release of the index, of 0.95, which is quite accurate if we consider that the series is an index expressed in levels fluctuating around a mean of 100. Indeed, the standardized ifo Business Climate Index is closely correlated with the first factor, as illustrated in Fig. 8.

Fig. 9 shows the model's prediction of another key variable commonly used to assess the current point of the German business cycle: industrial production (excluding construction). The series is expressed as an index based on the reference year 2015. Our nowcast has an RMSE, measured the day before the release, of 0.48. Considering the scale of the variable, it appears that, as for ifo, the model is able to produce an accurate prediction of the series.

In order to obtain an overview of the overall performance of the model beyond forecast errors in GDP, it is very informative to ask when the revisions to the

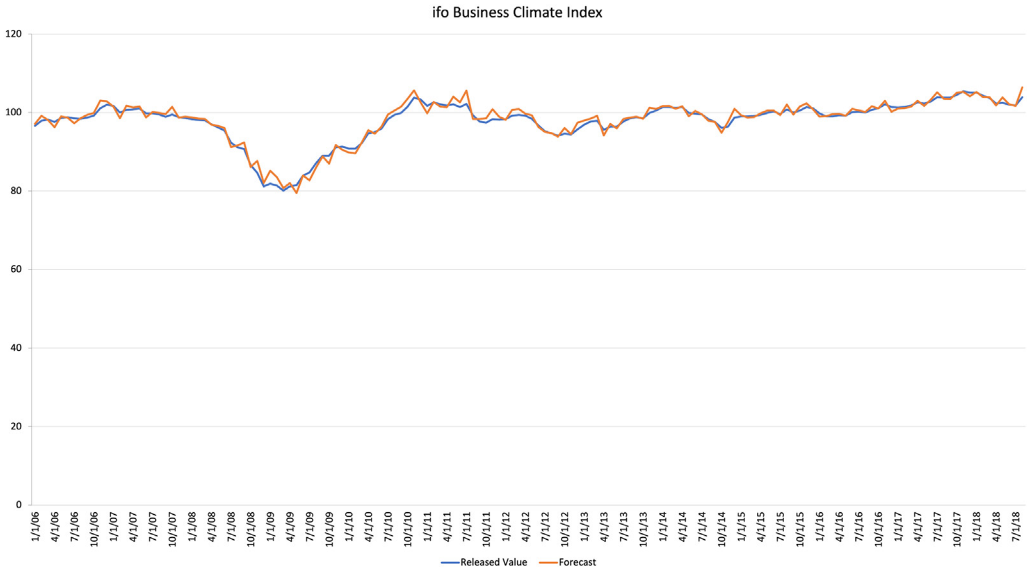


Fig. 7. Model prediction of the ifo Business Climate Index.

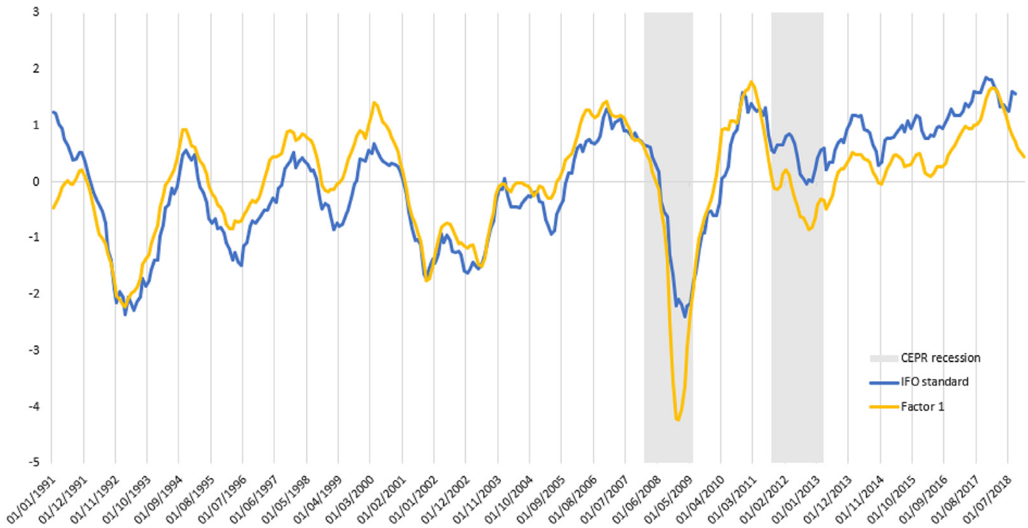


Fig. 8. First factor versus the ifo Business Climate Index.

nowcast were particularly large or particularly small. In other words, when was the model surprised by new data releases that differed from the model's predictions? A news index can help to answer these questions. As we have seen, the "news" can be defined as the model's surprise, that is the difference between the actual value of the variable released and the model's forecast for that release. Formally, the definition is as follows:

$$News_{j,t} = x_{j,t} - \mathbb{E}[x_{j,t}|\Omega_t] \tag{6}$$

where j refers to a specific variable included in the model. In order to construct the news index, we need to compute weights. As proposed by Leomborni (2014) and Caruso (2019), we use the weights estimated by the nowcasting model, shown in Eq. (5). The weights need to take into consideration where we are in the quarter. Hence, they need to be weighted using the following scheme:

$$W_{j,t} \begin{cases} \frac{33+d}{66} w_{j,t}^{NC} + \frac{33-d}{66} w_{j,t}^{BC}, & \text{if } 0 \leq d < 33 \\ \frac{99-d}{66} w_{j,t}^{NC} + \frac{d-33}{66} w_{j,t}^{FC}, & \text{if } 33 \leq d \leq 66 \end{cases}$$

where BC denotes backcast weights, NC denotes nowcast weights, FC denotes forecast weights, and d is the number of working days elapsed in the quarter.

Finally, in order to identify changes in the news over time, we need to aggregate daily values using a moving average:

$$NSI_t^h = \sum_{k=0}^{h-1} \sum_{j \in \mathbb{J}_{t-k}} W_{j,t-k} News_{j,t-k}$$

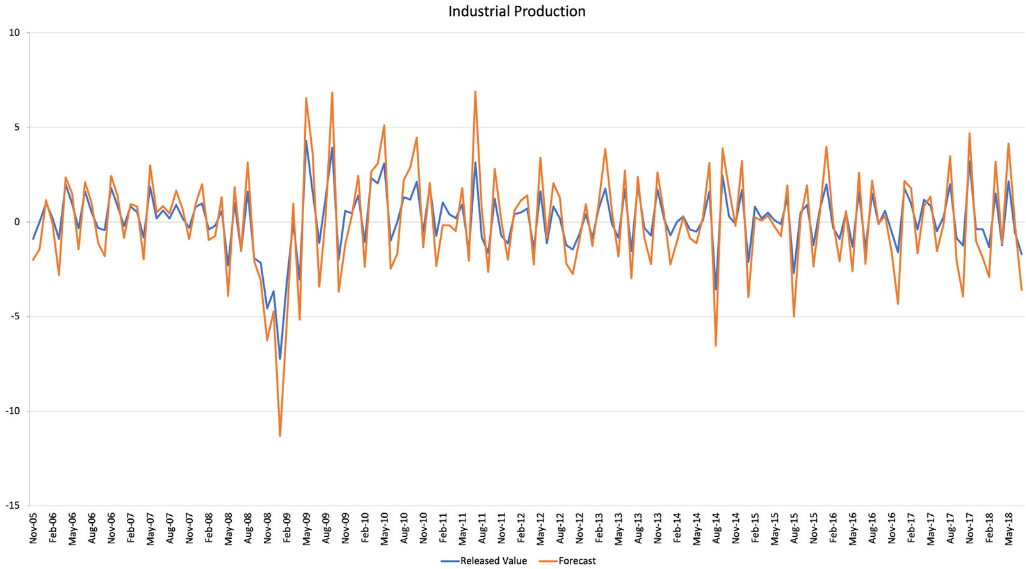


Fig. 9. Model prediction of industrial production (excluding construction).

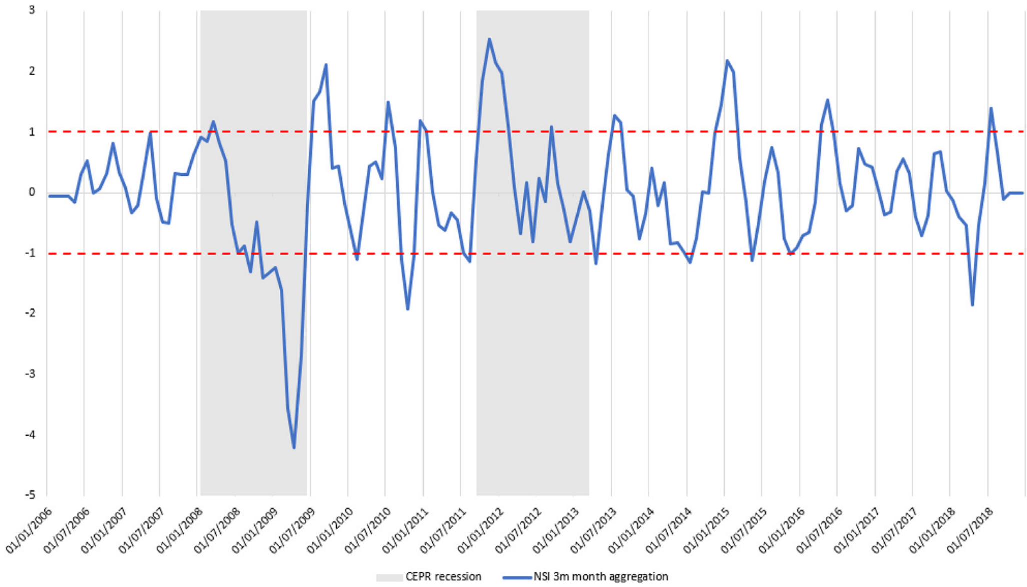


Fig. 10. News index.

where j always refers to the variable of interest at that given day, $\mathbb{J}$ is the list of variables available at a given day, and h is the rolling window in which the surprises are accumulated ($h = 22, 44, 66$, meaning 1, 2, or 3 months, respectively).

Fig. 10 shows a reconstruction of the news index since 2006. As expected, the index has stationary fluctuations around zero. Notice the higher volatility around recessions. The higher volatility of the news index during recessions is in line with our finding that forecasting GDP is particularly difficult during downturns.

7. Conclusion

The paper developed a nowcasting model for the German economy. We considered different models, including and excluding nominal and financial variables and including and excluding US and euro area variables. We also considered different model specifications.

The preferred model includes 24 real, domestic variables and a euro area factor. Important variables are industrial production, services and construction indicators, surveys, labor market, and trade variables. The composite index of euro area real economic conditions is estimated by an auxiliary model including a wealth of euro area information. A US factor does not add forecasting power beyond the euro area factor.

The model produces real-time updates for the current period and short-term future of all included variables. It also decomposes each update as the sum of nowcasting errors (the "news") associated with each variable and their impact. A byproduct of the analysis is the estimation of two common factors, the first of which can be considered a coincident index of the German economy, and the second an index of the model's "news".

An interesting result from our paper is that, similar to earlier results from other countries, financial variables do not help to improve the nowcasting performance of GDP, although the DAX stock market index is coincident with the estimated first factor. This suggests that, although stock prices are contemporaneously correlated with the business cycle, they do not convey any leading information for it.

The forecasting performance of the preferred dynamic factor model is quite precise compared to a naive benchmark and to existing models applied in practice. This highlights the usefulness of our nowcasting model, helping decision makers to base their choices on an accurate view of "where the German economy stands now".

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. PCA of the variables

To describe the correlation structure of our data, it is interesting to report results from principal component analysis (PCA). As shown by Giannone et al. (2004), real macroeconomic variables are strongly correlated. This motivates the empirical methodology in which each series is modeled as a linear function of a few common factors that capture information from many series.

For each of our monthly variables, Table 4 shows the fraction of their variance explained by each of the first four principal components, as well as the fraction explained by their cumulative sum. A few characteristics emerge from the results:

1. The first principal component (PC) explains a large part of the variance of many of the domestic real variables and surveys.
2. This is not the case for some of the variables typically focused on by conjuncture analysts, such as retail sales or passenger car registrations. The reason is that these variables are very volatile. However, they are of interest because of their timeliness.
3. The second PC is mostly relevant for survey indicators and has less additional explanatory power for the variance of the hard data.
4. The foreign factors are largely explained by the first PC, and so are the euro area variables.
5. The variance of the nominal and financial variables explained by all PCs is close to zero, indicating minimal correlation between the real side and the nominal side of the economy.

Appendix B. Estimation of the foreign factors

The US and euro area factors are monthly variables which are estimated, respectively, from the US and euro area models in Bańbura and Modugno (2014) and Giannone et al. (2008).

The US model is a two-factor model, like the one proposed in this paper, and includes US variables only. The euro area model is slightly more complex and includes variables from a number of euro area countries, as well as euro area aggregates. The model imposes restrictions on the correlation matrices in order to compute one euro area factor, one factor common to all "soft" variables, and one common to all "hard" variables.

The augmented factor is computed in real time, which implies that every time there is an update in the euro area model as a consequence of a new data release, we treat this as a new release of the euro area factor in the German model and update the estimate of the factors in the German model and the nowcasts accordingly. We do the same for the US factor.

Appendix C. The state-space representation – matrices

We present the details of the state-space representation, using $p = 2$, $r = 1$, N monthly variables, and only one quarterly variable.

The measurement equation has the following matrix form:

$$\begin{pmatrix} y_t \\ y_t^q \end{pmatrix} = \underbrace{\begin{pmatrix} \mu \\ \mu_q \end{pmatrix}}_{\bar{\mu}} + \underbrace{\begin{pmatrix} \Lambda & 0 & 0 & 0 & 0 & I_N & 0 & 0 & 0 & 0 & 0 \\ \Lambda_q & 2\Lambda_q & 3\Lambda_q & 2\Lambda_q & \Lambda_q & 0 & 1 & 2 & 3 & 2 & 1 \end{pmatrix}}_{B(\theta)} \times \underbrace{\begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \varepsilon_t \\ \varepsilon_t^q \\ \varepsilon_{t-1}^q \\ \varepsilon_{t-2}^q \\ \varepsilon_{t-3}^q \\ \varepsilon_{t-4}^q \end{pmatrix}}_{\alpha_t}, \tag{7}$$

Table 4
PCA: Fraction of the variance of each variable that is explained by the first four principal components.

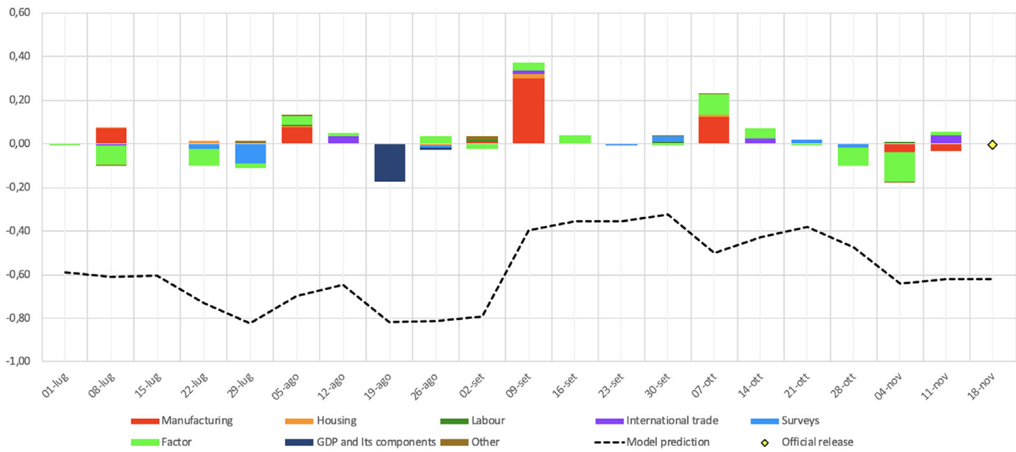
N	Description	PC 1	PC 2	PC 3	PC 4	Sum
1	ZEW Economic Sentiment	**0.45**	0.15	0.10	0.04	0.62
2	ifo Business Climate Index	**0.41**	0.38	0.04	0.01	0.85
3	ifo Business Situation: Industry and Trade	0.25	**0.48**	0.10	0.02	0.86
4	PMI: Manufacturing	**0.62**	0.11	0.05	0.01	0.82
5	PMI: Services Business Activity	**0.44**	0.11	0.08	0.03	0.65
6	Consumer Climate Index	0.29	**0.37**	0.04	0.00	0.72
7	BA-X Job Index	**0.21**	0.00	0.04	0.04	0.30
8	Total Domestic Employment	**0.15**	0.09	0.09	0.00	0.33
9	Passenger Car Production	**0.15**	0.00	0.00	0.00	0.15
10	Job Vacancies	**0.36**	0.03	0.04	0.01	0.44
11	Passenger Car Registrations	0.00	0.02	**0.03**	0.00	0.05
12	Retail Sales Index excluding Autos	0.02	0.01	0.10	**0.43**	0.56
13	New Orders: Manufacturing	**0.17**	0.15	0.00	0.01	0.33
14	Total Manufacturing Sales	**0.35**	0.19	0.02	0.01	0.57
15	Industrial Production excl Construction	**0.34**	0.14	0.00	0.02	0.51
16	Industrial Production Construction	0.04	0.10	**0.37**	0.01	0.51
17	Exports of Goods	**0.11**	0.05	0.02	0.04	0.22
18	Imports of Goods	**0.10**	0.03	0.02	0.01	0.16
19	Total Housing Permits	0.00	**0.01**	0.00	0.01	0.02
20	EA factor	**0.77**	0.00	0.00	0.00	0.77
21	US factor	**0.56**	0.02	0.00	0.04	0.62
22	EA 18: Ind Production exl Construction	**0.37**	0.15	0.00	0.01	0.52
23	EA 18: Manufact New Orders	**0.23**	0.14	0.00	0.00	0.37
24	EA 18: Manufact Turnover	**0.51**	0.22	0.02	0.01	0.76
25	EA 18: Ind Production Construction	0.06	0.11	**0.44**	0.01	0.61
26	EA 18: Retail Sales	0.04	0.01	0.05	**0.73**	0.83
27	EA 18: Import	**0.37**	0.11	0.03	0.02	0.53
28	EA 18: Exports	**0.36**	0.20	0.00	0.00	0.56
29	EU 27: New Passengers Car Registration	**0.16**	0.01	0.01	0.03	0.21
30	EA: PMI Manufact	**0.62**	0.06	0.09	0.03	0.8
31	EA: PMI Business Act	**0.50**	0.04	0.11	0.04	0.69
32	EA 18: Business Climate Ind	**0.40**	0.36	0.02	0.00	0.78
33	EA 18: Consumer Confidence Ind	**0.04**	0.01	0.00	0.01	0.06
34	Money Supply: M2	0.01	**0.03**	0.00	0.00	0.05
35	Harmonized Index of Consumer Prices	0.03	0.01	0.03	**0.07**	0.13
36	Harmonized PPI: Industry excl Construction	**0.21**	0.01	0.05	0.06	0.32
37	Negotiated Hourly Earnings	0.00	0.00	**0.01**	0.00	0.01
38	Negotiated Monthly Earnings	0.00	**0.01**	0.00	0.00	0.01
39	WTI price oil	**0.04**	0.02	0.01	0.03	0.09
40	Yield on All outstanding Debt	**0.08**	0.00	0.01	0.00	0.09
41	Base Rate EOP	**0.12**	0.00	0.02	0.00	0.14
42	Exchange rate EUR–USD	0.00	0.00	0.01	**0.07**	0.08
43	Stock Market Index: DAX	0.01	**0.08**	0.00	0.02	0.10
44	S&P 500 Price	0.02	**0.05**	0.01	0.00	0.08
45	Variance PC_i/ Sum of the variance	0.22	0.11	0.07	0.60	0.46

Notes: This table reports the fraction of the variance of each monthly variable that is explained by each of the first four principal components of the data set. The last column shows the total fraction of the variance of each variable explained by the first four principal components. The last row shows the fraction of the total variance of the data set that is explained by each of the first four principal components taken together. For each variable, the principal component that explains the highest fraction of the variance is indicated in bold.

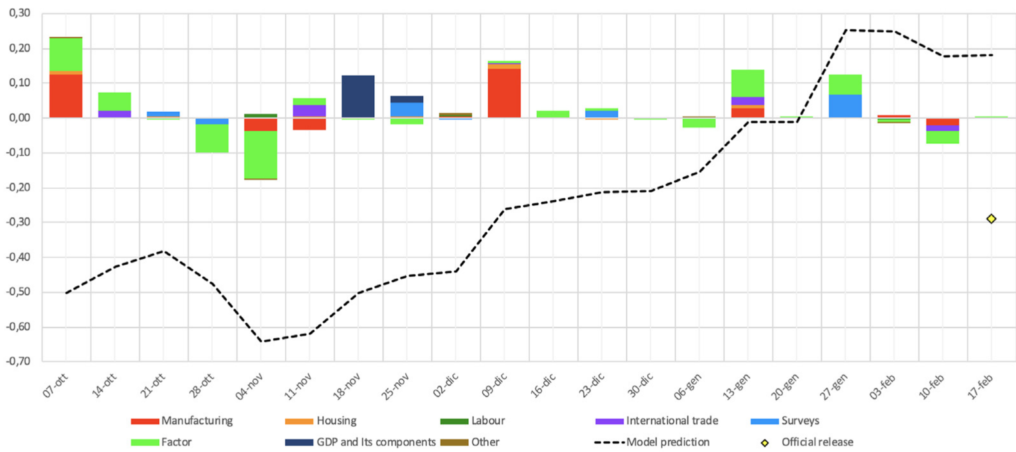
while the transition equation has the following form:

$$
\begin{pmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ \varepsilon_t \\ \varepsilon_t^q \\ \varepsilon_{t-1}^q \\ \varepsilon_{t-2}^q \\ \varepsilon_{t-3}^q \\ \varepsilon_{t-4}^q \end{pmatrix}
=
\underbrace{\begin{pmatrix}
C_1 & C_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & diag(\rho_1, \dots, \rho_N) & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \rho_q & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{pmatrix}}_{C(\theta)}
\times
\begin{pmatrix} f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ f_{t-5} \\ \varepsilon_{t-1} \\ \varepsilon_{t-1}^q \\ \varepsilon_{t-2}^q \\ \varepsilon_{t-3}^q \\ \varepsilon_{t-4}^q \\ \varepsilon_{t-5}^q \end{pmatrix}
+
\underbrace{\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ e_t \\ e_t^q \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}}_{\eta_t},
\tag{8}
$$

where $\varepsilon_t = (\varepsilon_{1,t}, \dots, \varepsilon_{N,t})'$ and $e_t = (e_{1,t}, \dots, e_{N,t})'$.



(a)



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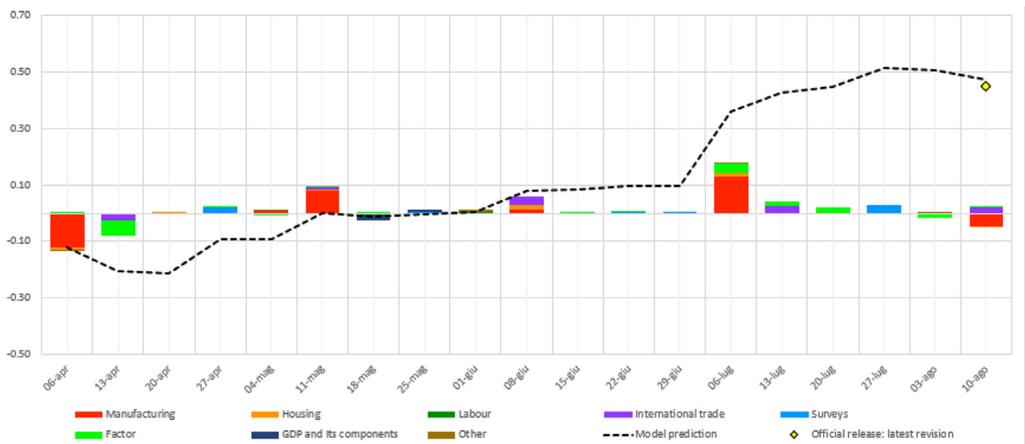

(c)

Fig. 11. (a) Contribution of news to forecast revisions for 2011Q3. (b) Contribution of news to forecast revisions for 2011Q4. (c) Contribution of news to forecast revisions for 2018Q2. All three charts are for Model II (i.e. the model with the euro area factor).

The state-space representation can be easily modified to include an arbitrary number of quarterly variables and an arbitrary number of factors and lags.

Appendix D. Event studies for additional quarters

See Fig. 11.

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