Nowcasting German GDP

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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 foreign variables 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 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. Indeed, the term nowcasting is borrowed from meteorologists, and it is a contraction of the words "now" and "forecasting". 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) (GRS from now on) was the first to formalize the problem in a comprehensive framework. The recent literature builds on that contribution. GRS propose a framework that allows for the use of a large number of data series, possibly available at different frequencies and with different information lags. It proposes a solution to three problems related to nowcasting. First, the so called 'curse of dimensionality' due to the potential relevance of many series beyond the few that can be considered in small models such as 'bridge equations'. Today, many surveys are available as well as many indicators on various sectors of the economy. Exploiting this information implies the use of a large model. To avoid a proliferation of parameters, there is a need to enforce parsimony. This is achieved by modeling each series as a function of a few common unobserved factors, in the tradition of Forni et al. (2000), Stock and Watson (2002a) and Stock and

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Watson (2002b). As the literature suggests, factor models have desirable properties when there is strong comovement between economic data. Second, the problem of the non-synchronicity of data releases, which implies that the estimates have to be updated, at each release, on the basis of a panel with a jagged edge due to missing observations. Third, the problem of including data recorded at different frequencies, typically monthly and quarterly. The second and third problems are solved by considering the state space representation of a parametric factor model and updating the factor estimate via the Kalman filter while using the EM algorithm to deal with mixed frequency data. The asymptotic properties of such a model under some general conditions have been analysed by Doz et al. (2011) while the EM algorithm for a general pattern of missing data has been designed by Bańbura and Modugno (2014).

Following Bańbura et al. (2013), this paper develops a state of the art nowcasting model for the German economy which is implemented on a platform for the real-time tracking of relevant variables and can be used for policy on a regular basis. The interesting feature of the approach is that it allows us to model the dynamic interaction between all variables of interest and that it produces short-term predictions for all of them while tracking forecast revisions in relation to "errors" in each variable. Such errors are model-based news and drive the updating process. Therefore, although the model is reduced form, it is not a black box, but allows us to track the information flow in a comprehensive and transparent way. Such tracking mimics the judgmental evaluation typically performed by business economists. However, it does so by means of an algorithm with no human touch beyond, of course, the design of the algorithm itself and the initial choice of the variables.

Confirming the results of multiple papers, we show that the progressive arrival of data improves the forecast error of GDP throughout the quarter, supporting 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.

The model is tested against a number of alternatives. It produces precise forecasts for GDP and for other variables closely watched by the market, as for example the ifo business climate index. We study the value of including financial indicators as well as Euro Area and US variables for the accuracy of the model. The results indicate that foreign variables prove helpful for nowcasting while financial variables do not. 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 for US data).

The next section presents the data. The methodology and the platform are 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 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 the sample from January 1991 to September 2018. The variables are shown in Table 1 which indicates, for each of them, 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.[1]

The upper panel of Table 1 shows 24 real variables. They include a number of surveys, for example the ifo business climate index and the German PMI index. These series 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 stages of the reference quarter. In addition to GDP, we also 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. Introducing auxiliary factors is a parsimonious way to take into account the effect of foreign economic developments on the German economy. They 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.[2]

The third panel of Table 1 contains twelve real variables related to the Euro Area. This represents an alternative to including auxiliary factors for foreign activity. They include a number of surveys and timely indicators, such as Euro Area PMIs, business climate index and consumer confidence index as well as data on actual realizations such as industrial production.

The lower panel of Table 1 shows twelve 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 since all are available daily. To incorporate them in the monthly model, end of period values are used.

[1] 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.

[2] The two factors are estimated via two separate dynamic factor models applied, respectively, to Euro Area and US data. Additional information on the models on which the foreign factors are estimated is provided in the Appendix.

Table 1: Data set: German variables, EA economic activity, 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 Idx: 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	SP 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 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.

Table 2: 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	SP 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 dataset. 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 dataset that is explained by each of the first four principal components taken together. For each variable, the fraction of the variance explained by that one of the four principal components which explains most of the variance is indicated in bold.

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 which capture information from many series.

For each of our monthly variables, Table 2 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 which are 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 principal component is mostly relevant for survey indicators and has smaller 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.

Later in the paper we will use some of these results to interpret the performance of our model for the nowcast of different variables.

3 The nowcasting model and the platform

Let us denote $y_t^m = (y_{1,t}^m y_{2,t}^m y_{N_m,t}^m)'$ 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. 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 Forni et al. (2000) and Stock and Watson (2002a).

We have:

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

where F_t is a r x 1 vector of unobserved common factors with r being the number of common factors, $0 < r < N_m + N_q$, N_m is the number of monthly variables and N_q the number of quarterly variables, 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. The technical solution for these problems is described in the Appendix.

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 i-th variable as $\mathbb{E}[y_{i,t} | \Omega_\nu]$, the expectation of $y_{i,t}$ 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, $\mathbb{E}[y_{i,t}|I_{\nu+1}]$ will be 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, $\hat{\theta}$, the nowcasts, the *news*, and the corresponding weights can be obtained via a run of the Kalman filter and smoother.

As has been shown in multiple papers, the value of nowcasting models consists in their timeliness: model output can be recalculated whenever any new information arrives and by doing so the accuracy of the model's predictions can be continuously improved. For this reason we have implemented the model on the automated platform built by Now-Casting Economics, which allows us to gather and store its results so that we can analyse its real time performance. The following diagram illustrates the platform.

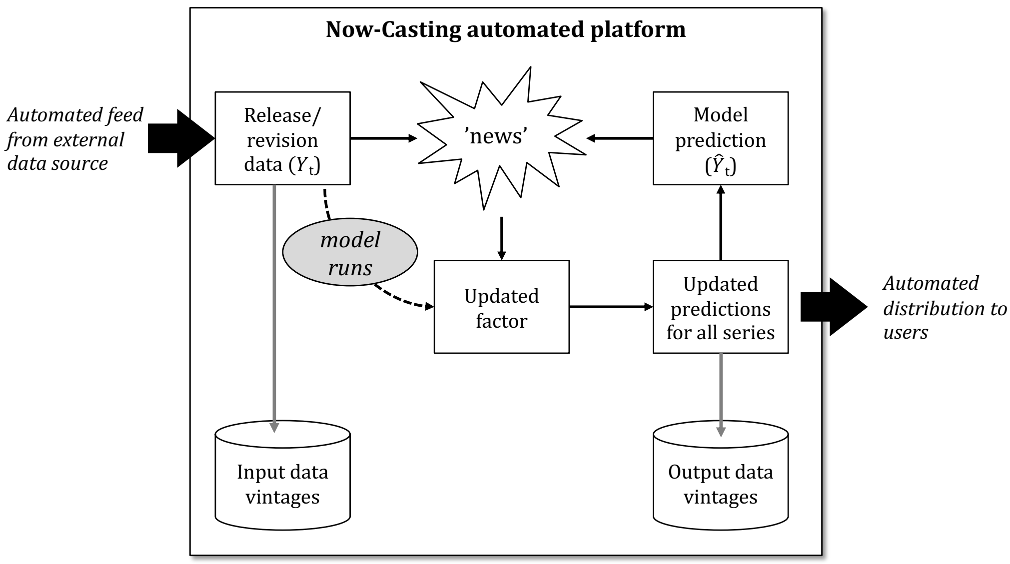

Figure 1: The Now-Casting platform

When any of the series used in the model is released the new information is automatically delivered to the Now-Casting Economics platform by an external data vendor, triggering the model to run. The difference between the new release value and the models prior expectation of that release value in other words the "news" is used to update the factor and consequently to update the models predictions for all of the input series. These new output values are automatically transmitted to the models users. When prior period values for any of the input series are revised, this new information triggers an update of all of the models outputs in exactly the same way as for the publication of a new release value. All of the new values for inputs and outputs are stored in a database, with time stamps, so that the database stores a full history of input and output data "vintages".

4 Empirical analysis of different models

We consider a number of different models (refer to Table 1 for variables' specification):

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) including real variables and surveys.
3. *Model III*. Model II augmented by a factor obtained by the estimation of a US model including real variables and surveys (see Appendix).
4. *Model IV*. Model I augmented by Euro Area variables (this model differs from Model II as Euro Area information is included as 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 to two. This choice is informal and based on the principal component analysis reported in Table 2 which points to there being very little marginal contribution from additional principal components. We will report 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.

As a first illustration of how well we track GDP, Figure 2 plots fully revised actual GDP growth rates against the nowcast from *Model I* one day prior to the release.

Table 3 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 "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 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 with time. Notice also that all models outperform the AR(1). Models including Euro Area

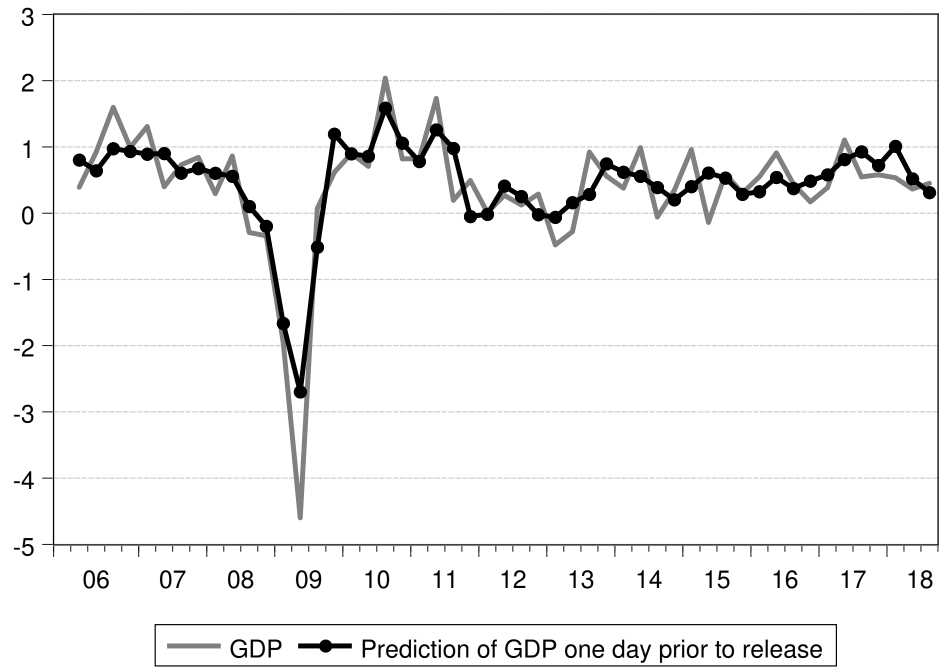

Figure 2: Realized GDP growth versus prediction from the baseline model

Table 3: Comparison of RMSEs relative to the AR(1) benchmark

	Forecasting		Nowcasting			Backcasting
Model	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 a 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 refers to the RMSEs 32 weeks prior to the release date.

variables or Euro Area factors perform best and outperform both Model I and the bridge equation model which include only domestic variables. Nominal and financial variables and the US factor do not seem to add forecasting power.

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 factor or as individual Euro Area variables is minimal.[3]

In general, all forecasts based on the factor models are highly correlated as illustrated in Figure 3

[3]For the live version of the platform we opt for Model II as our preferred model since it does better until 8 weeks before the release.

which plots the pseudo real-time nowcast for all models against revised GDP quarterly growth.

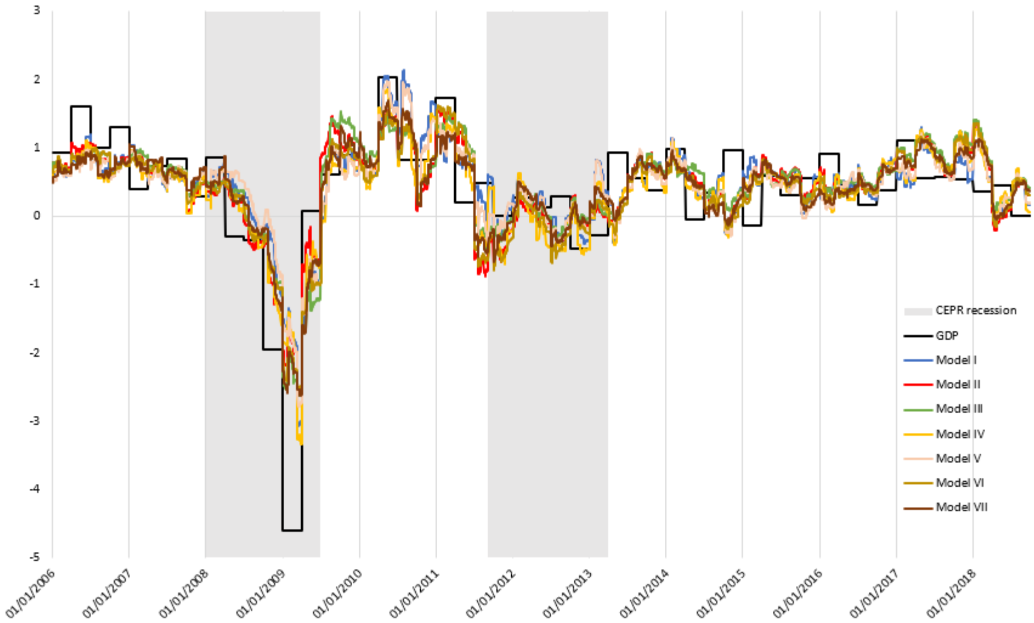

Figure 3: Realized GDP versus nowcast reconstruction

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, blue line is Model I, red line is Model II, green line is Model III, yellow line is Model IV, pink line is model V, light brown is Model VI and dark brown line is Model VII.

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.

Figure 4 shows the average RMSE from the beginning to the close of the quarter for Model I and Model II against the AR(1). The forecast error of the two models decreases over time as more information becomes available, confirming results obtained in the literature for several countries (Angelini et al. (2011), D'Agostino et al. (2013), Anesti and Miranda-Agrippino, 2017, Daniela (2017), Bragoli Daniela and Michele (2015), Daniela and Jack (2016) and Alberto (2015)). The Euro Area factor included in Model II helps at the forecast and nowcast horizon but worsens results at the backcast horizon. Notice, however, that differences are small.

Figure 5 shows the nowcast reconstruction in pseudo real-time for Model I and Model II against quarterly GDP.[4] It shows that the differences in performance between the two models are explained by the two recessions in our sample. Model II outperforms Model I in the down-turn and recovery of 2008-2009 reflecting the global nature of the crisis. However, it does worse in 2011 when Germany did not follow the rest of the Euro Area in the debt related recession.

Figure 6 confirms this result by showing the squared forecast error (SFE) evolution computed at

[4]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 years 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 revisions histories are not available. We call this a pseudo real-time reconstruction.

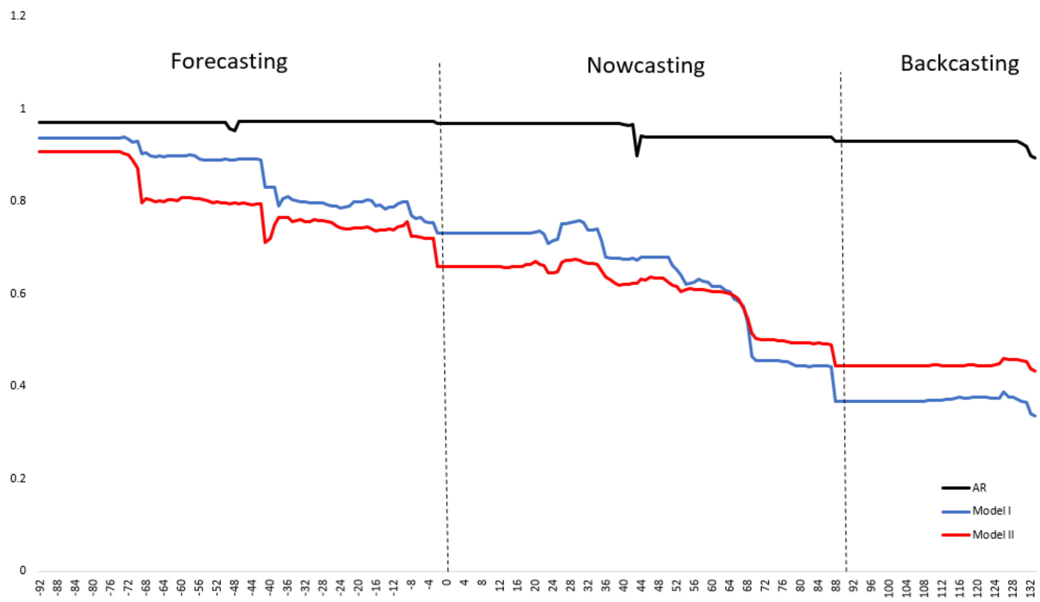

Figure 4: RMSE German dynamic factor model versus statistical benchmark

Notes: This Figure shows the RMSE evolution along the quarter of the preferred Model versus the baseline and the AR(1). The black line is the AR(1), blue line is Model I, red line is Model II.

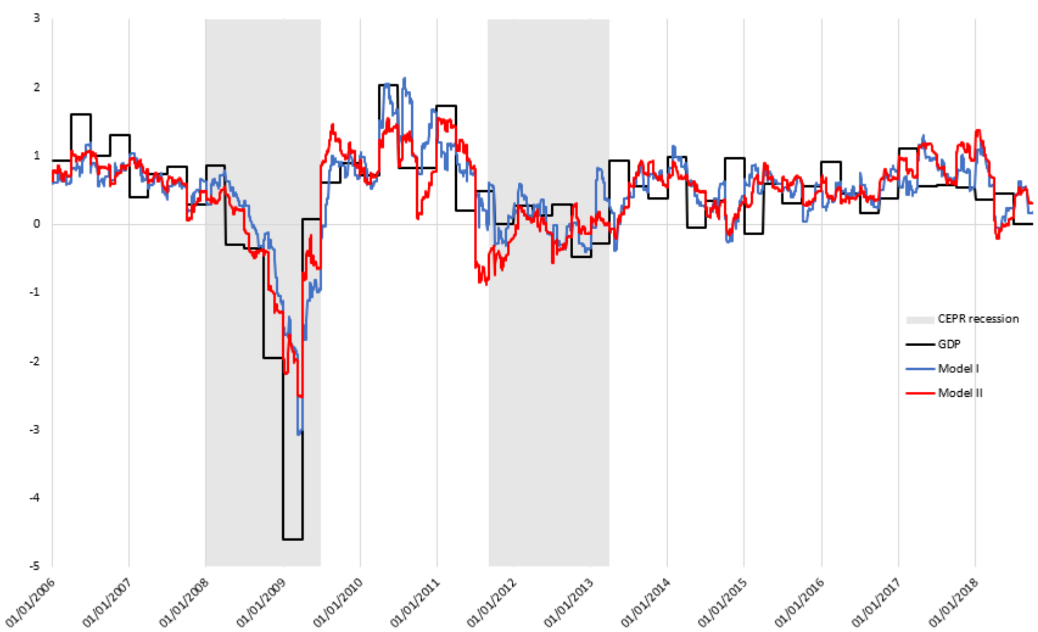

Figure 5: Realized GDP versus German dynamic factor model

Notes: This Figure shows the nowcast reconstruction in pseudo real-time of Model II versus the Baseline. The black line is the GDP, blue line is Model I, red line is Model II.

each release. Both Model I and Model II are surprised by the onset of the 2008 recession although Model II does better than Model I. In 2011 the error is smaller and Model I does very well.

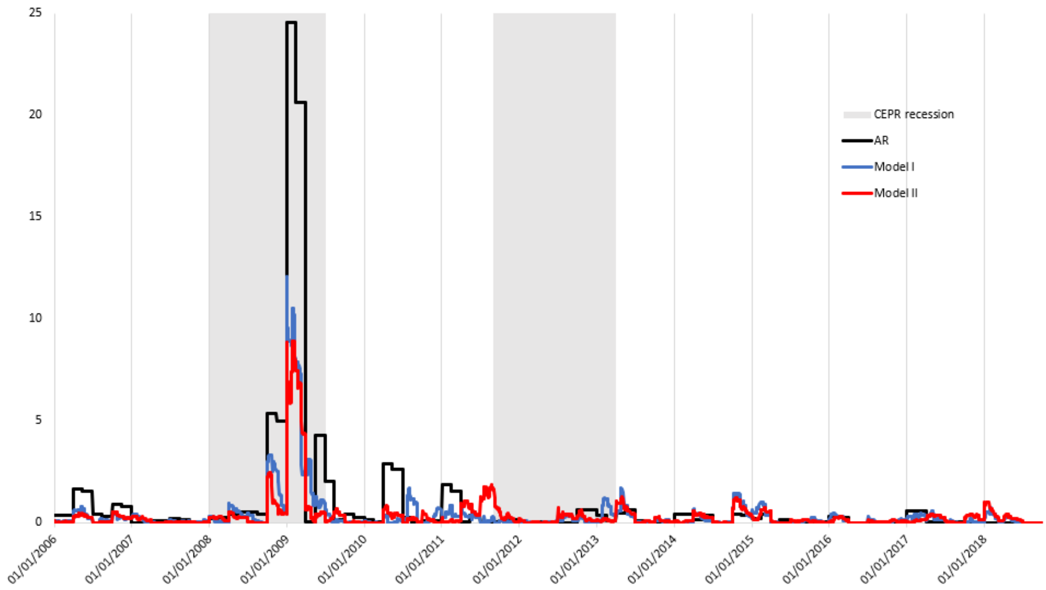

Figure 6: SFE over time

Notes: This Figure shows the SFE at each release of the preferred Model II versus the baseline Model I and the AR(1). The black line is the AR(1), blue line is Model I, red line is Model II.

We now study the impact of individual variables on the nowcast for Model II.

Figure 7 shows the average impact of each variable on predicted GDP during the nowcasting period. 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 equation 5. In line with 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, similarly 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, as, 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 effect of news on forecast revisions, Figures 8 and 9 show a replicated real-time nowcast of GDP for the third quarter of 2008 for 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 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.

The chart shows that 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. This emphasizes the role of Euro Area economic development as a leading indicator for German GDP during the financial crisis. Apart from

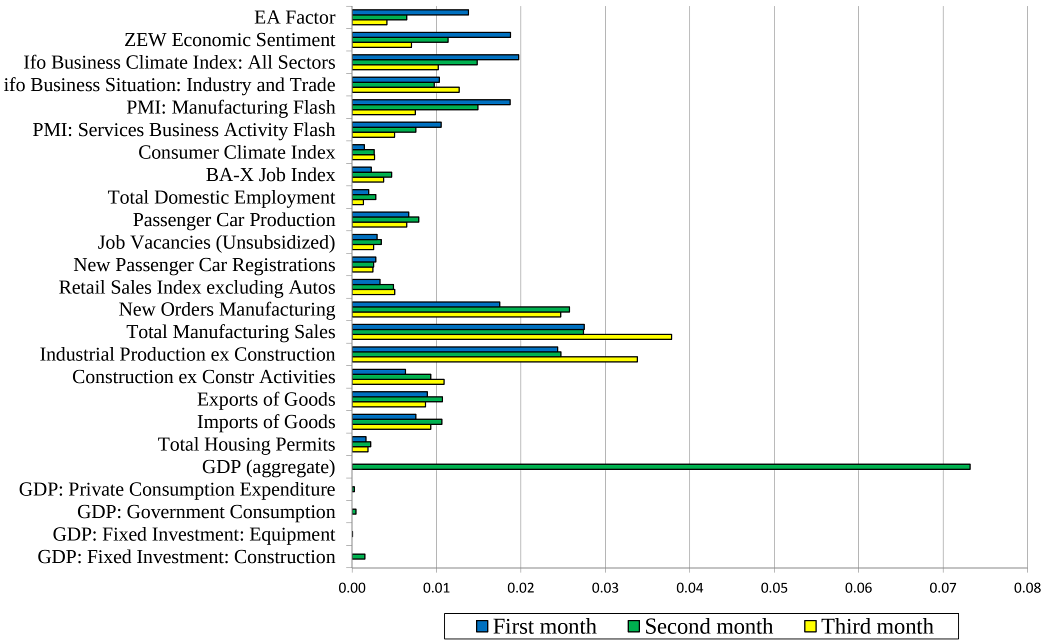

Figure 7: Impact of individual series on predicted GDP

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) 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.

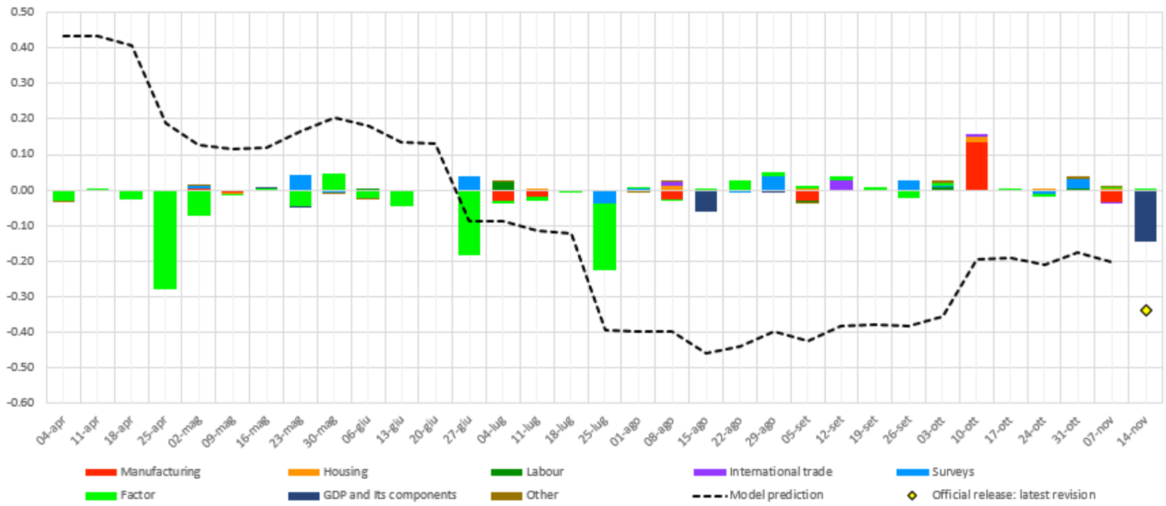

Figure 8: Contribution of news to forecast revisions: 2008Q3

We can repeat the same exercise for the second quarter of 2018. Here the nowcast at the beginning of the quarter is dragged down by the manufacturing releases and the Euro Area factor but already in May the signal becomes positive, consistent with later releases for trade and labor market variables. By June the nowcast moves upward and by July the model produces a very accurate prediction of GDP which is released a month later.

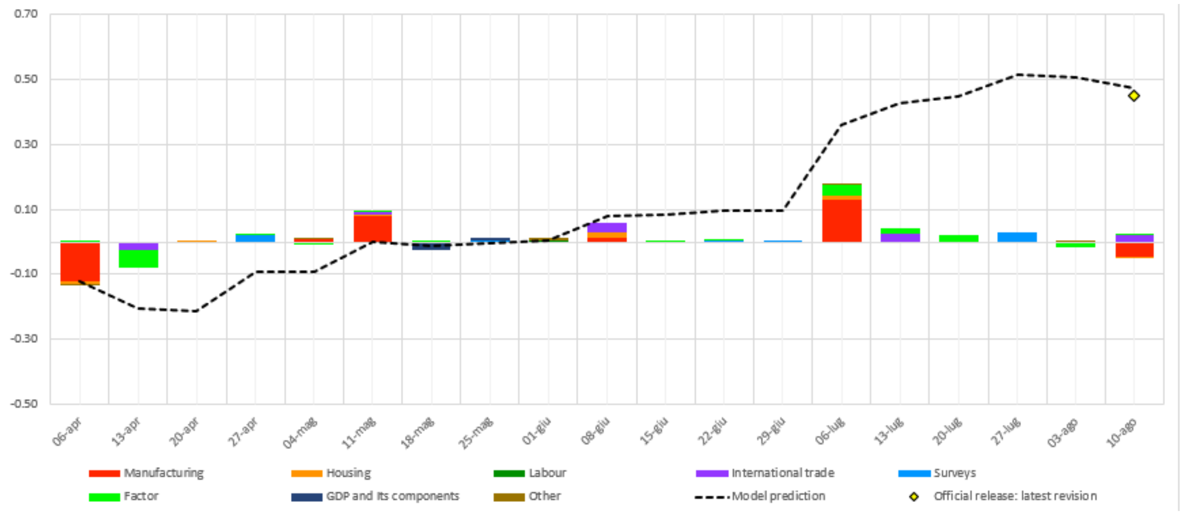

Figure 9: Contribution of news to forecast revisions: 2018Q2

4.2 Nowcast and financial variables

As we have seen earlier in Section 4, the model that contains nominal and financial variables does worse than the model with real variables only. This may seem puzzling since it is normally assumed that financial variables are forward looking and should therefore contain advance information on the real economy. Let us provide some descriptive statistics to shed light on this problem.

Figure 10 plots the first estimated factor, 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.

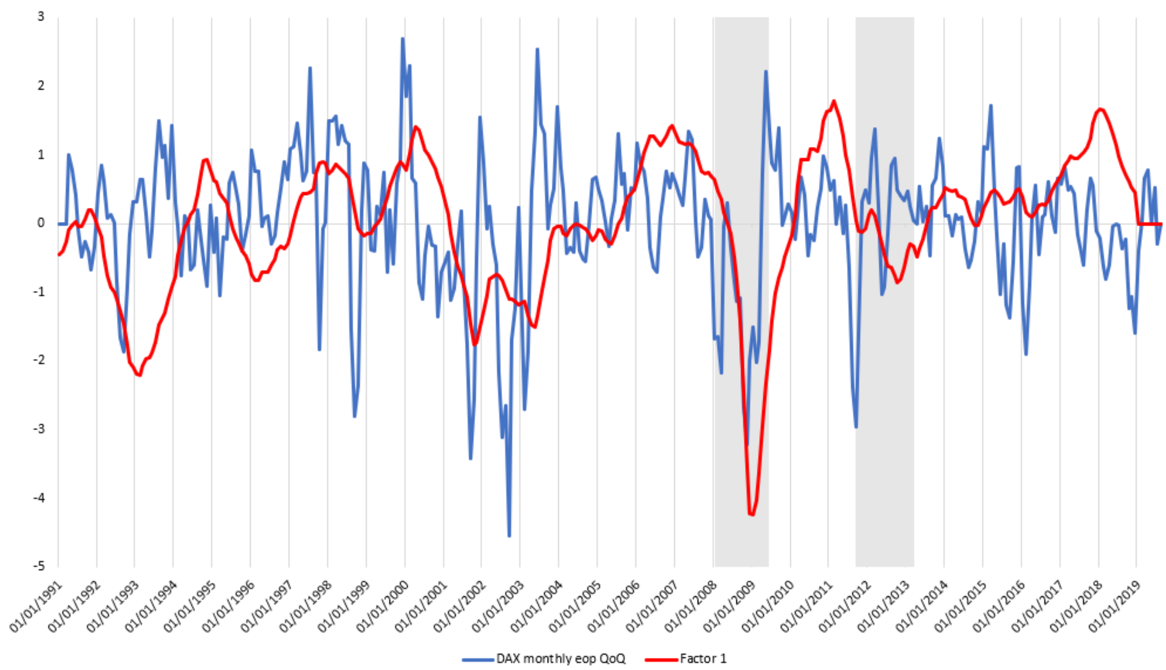

Figure 10: DAX versus Factor

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. This explains why the model's performance does not improve when financial variables are included.

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 in 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. Results are reported in Table 4.

Table 4: Model average RMSE against the AR(1) benchmark

	Forecasting		Nowcasting			Backcasting
Model	32 weeks	26 weeks	20 weeks	14 weeks	8 weeks	2 weeks
Model I	0.97	0.92	0.80	0.77	0.73	0.71
Model II	**0.93**	**0.83**	0.72	0.69	0.67	0.66
Model III	0.98	0.85	0.74	0.71	0.70	0.69
Model IV	1.01	0.93	0.74	0.70	0.62	0.60
Model V	0.97	0.93	0.81	0.79	0.75	0.74
Model VI	0.94	0.86	0.77	0.75	0.73	0.72
Model VII	1.02	0.94	0.75	0.70	0.62	0.60
Average all	0.96	0.90	0.76	0.73	0.68	0.66
Average $r = 2$, $p = 2$	0.94	0.85	**0.70**	**0.65**	**0.52**	**0.47**

Notes: This table reports the average RMSE for each of the seven models specified in Section 4 (see page 9), the average being calculated from four different parametrizations in each case. The RMSE is shown relative to the RMSE of an AR(1). Additionally we include the results ("Average all") from the average across all the models and all the possible specifications. Lastly, we show the average of all seven models using the standard parametrization ("Average $r = 2$, $p = 2$"). Relative RMSEs are reported for different dates relative to the release date of German GDP. For example, the RMSEs at 32 weeks refers to the RMSEs 32 weeks prior to the release date.

Two results emerge from this analysis. First, averaging across different specifications and models does not improve on the performance of the best model with fixed $p = 2$ and $r = 2$. Indeed the average for Model II, the best model, performs slightly worse but very close to Model II (see Table 3). 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 is also in contrast to results from the forecasting literature. This is explained here by the fact that, as seen in Table 3, all models have a relatively similar nowcast performance. Notice that the best factor model performs slightly better than an average across models which suggests that averaging across variables via factor extraction is more efficient than averaging across models.

6 Overall performance and the "news index"

Since our model produces predictions for all the included variables, it is interesting to report some results related to variables other than GDP.

Let us for example examine the model's prediction of the ifo business climate index which is a timely survey closely watched by the market. Figure 11 reports the index and the model's prediction the day before the official release, as downloaded from the Now-Casting Economics platform. The figure shows that the model tracks the index quite well. Indeed, the live version of the model, which has run since October 2018, has a 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.

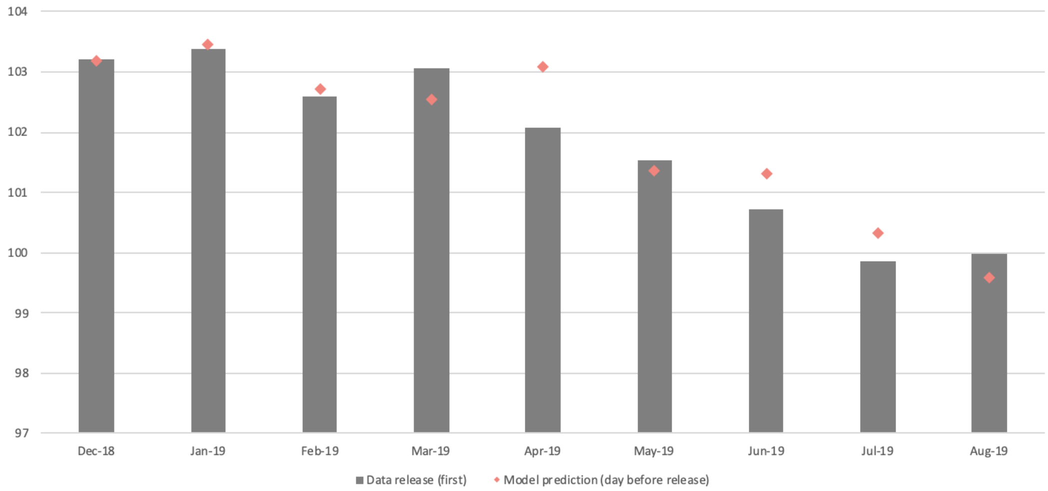

Figure 11: Model prediction of the ifo business climate index

Indeed the standardized ifo business climate index is closely correlated with the first factor as illustrated in Figure 12.

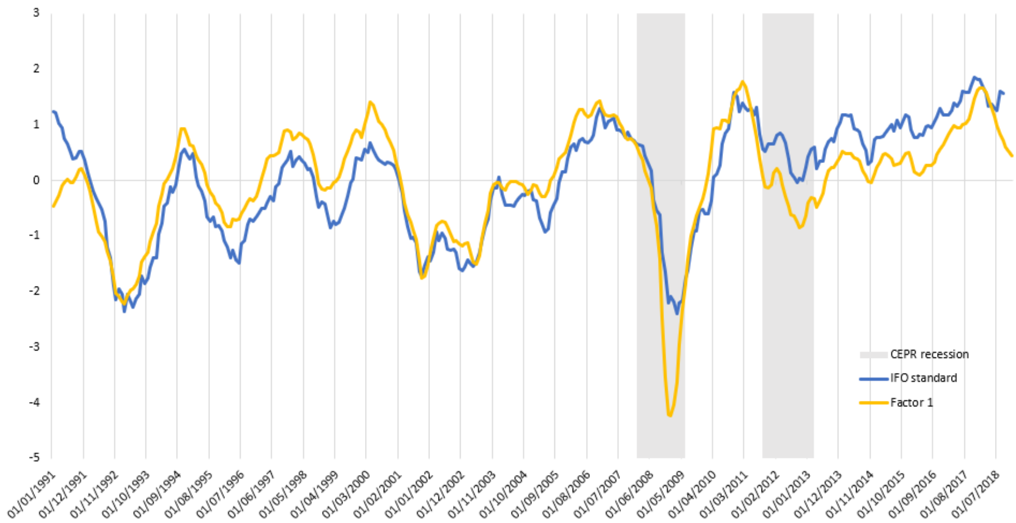

Figure 12: First factor versus ifo business climate index

Figure 13 shows the model's prediction of another key variable, industrial production excluding construction again the day before the official release. The series is expressed as an index based on a 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.

To obtain a view of the model's performance in relation to all the series rather than in relation to GDP specifically, it is interesting to construct an index based on the model's "news". As we have seen, the "news" can be defined as the model's surprise, that is the difference between the actual

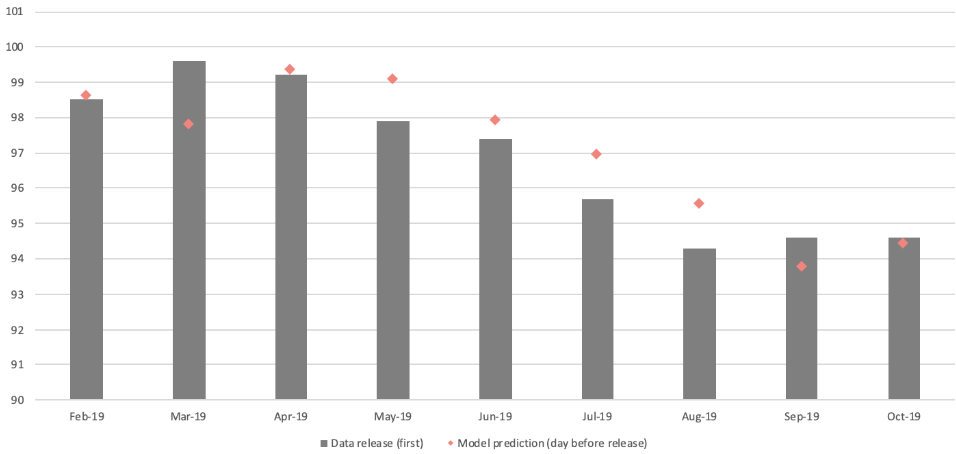

Figure 13: Model prediction of the Industrial Production excluding construction

value of the variable released and the model's forecast for that release. Formally, the definition is:

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

where j refers to a specific variable included in the model. In order to construct the news index we need to compute the weights. As proposed by Leomborni (2014) and Caruso (2019) we can use the weights delivered by the nowcasting model, shown in equation 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 stands fore backcast weights, NC for nowcast weights, FC are the forecast weights and d is the number of working days elapsed in the quarter.

Finally, in order to identify changes in th news over time we need to aggregate daily values, which we do by taking a moving average, as follows:

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

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

Figure 14 shows a reconstruction of the news index since 2006. As expected, the index has stationary fluctuations around zero. Notice the higher volatility around recessions reflecting higher uncertainty around those events.

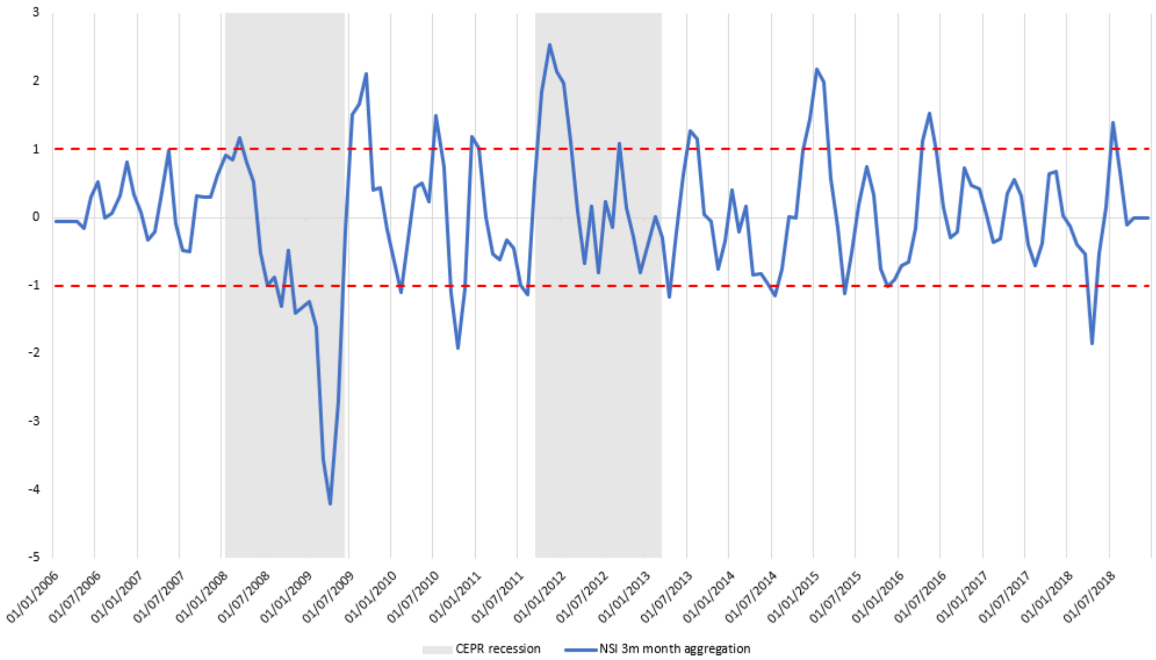

Figure 14: The news index

7 Conclusion

The paper develops a nowcasting model for the German economy. We consider different models, including and excluding nominal and financial variables and including and excluding US and Euro Area variables. We also consider different model specifications.

The preferred model, which has been implemented on the Now-Casting Economics platform, includes 33 variables reflecting the real economy only. These are industry, service and construction indicators, surveys, labor market and trade variables. We also include a composite index of Euro Area real economic conditions which is estimated by an auxiliary model including a wealth of Euro Area information.

The platform produces real-time updates for the current and short-term future of all included variables. It also decomposes each update as the sum of nowcasing errors (the "news") associated with each variable and their impacts. A by-product 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 financial variables do not help improving 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 cycle, they do not convey any leading information for it.

8 Appendix 1: Estimation of the foreign factors

The US and the Euro Area factors are monthly variables which are estimated, respectively, from the US and Euro Area models maintained at Now-Casting Economics.

The US model is a two-factor model as the one proposed in this paper and includes US variables only. The Euro Area model is slightly more complex and includes variables from Germany, Italy and

France as well as Euro Area aggregate variables. 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's estimates 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.

Details of the two models are available on the Now-Casting Economics website[5].

A Appendix II: 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:

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

while the transition equation has the following form:

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

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

[5] http://www.now-casting.com

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

References

Alberto, C. (2015). Nowcasting mexican gdp. *ECARES Working Papers*.

Anesti, Nikoleta, A. G. and Miranda-Agrippino, S. (2017). Uncertain kingdom: A new framework to nowcast gdp and its revisions. *Bank of England*.

Angelini, E., CambaMendez, G., Giannone, D., Reichlin, L., and Rünstler, G. (2011). Shortterm forecasts of euro area gdp growth. *The Econometrics Journal*, 14(1):C25–C44.

Bańbura, M., Giannone, D., Modugno, M., and Reichlin, L. (2013). Now-casting and the real-time data flow. In *Handbook of Economic Forecasting*, volume 2, pages 195–237. Elsevier.

Bańbura, M. and Modugno, M. (2014). Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data. *Journal of Applied Econometrics*, 29(1):133–160.

Bragoli Daniela, M. L. and Michele, M. (2015). The importance of updating: Evidence from a brazilian nowcasting model. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, 1(1):5–22.

Caruso, A. (2019). Macroeconomic news and market reaction: Surprise indexes meet nowcasting. *International Journal of Forecasting*, 35(4):1725 – 1734.

D'Agostino, A., McQuinn, K., and OBrien, D. (2013). Nowcasting irish gdp. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, 2012(2):21–31.

Daniela, B. (2017). Now-casting the japanese economy. *International Journal of Forecasting*, 33(2):390–402.

Daniela, B. and Jack, F. (2016). Nowcasting indian gdp. *University of East Anglia School of Economics Working Paper Series 2016-06*.

Doz, C., Giannone, D., and Reichlin, L. (2011). A two-step estimator for large approximate dynamic factor models based on Kalman filtering. *Journal of Econometrics*, 164(1):188–205.

Forni, M., Hallin, M., Lippi, M., and Reichlin, L. (2000). The generalized dynamic-factor model: Identification and estimation. *Review of Economics and Statistics*, 82(4):540–554.

Giannone, D., Reichlin, L., and Sala, L. (2004). Monetary policy in real time. *NBER Macroeconomics Annual*, 19:161–200.

Giannone, D., Reichlin, L., and Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. *Journal of Monetary Economics*, 55(4):665–676.

Leomborni, M. (2014). News index and asset return predictability. *Working paper*, pages 1–21.

Mariano, R. S. and Murasawa, Y. (2003). A new coincident index of business cycles based on monthly and quarterly series. *Journal of Applied Econometrics*, 18(4):427–443.

Pinkwart, N. (2018). Short-term forecasting economic activity in Germany: A supply and demand side system of bridge equations. Discussion Papers 36/2018, Deutsche Bundesbank.

Rapach, D., Strauss, J., and Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *Review of Financial Studies*, 23(2):821–862.

Stock, J. H. and Watson, M. W. (2002a). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97(460):1167–1179.

Stock, J. H. and Watson, M. W. (2002b). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2):147–162.

Timmermann, A. (2006). Forecasting combinations. *Handbook of Economic Forecasting*, 1(1):135–196.